University of Southampton

Faculty of Environmental and Life Sciences

Geography and Environmental Science

Mapping Spatial and Temporal Inequalities in Utilisation of Maternal and Newborn Care in Five East African Countries

by

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Thesis for the degree of Doctor of Philosophy

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Abstract

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Historically, maternal and newborn health (MNH) outcomes used to monitor progress in achieving global and national targets have been measured at an aggregate level, showing vast inequalities between and within countries. To ensure no one is left behind in improving health, researchers have called for the spatial and temporal disaggregation of MNH data. This thesis aims to generate high spatial resolution data over time that can be used to monitor progress in reducing inequalities amongst utilisation of key MNH services in the East African Community (EAC) region, including Burundi, Kenya, Rwanda, Tanzania, and Uganda.

Following a 'three-paper' format, the first paper in this thesis employs a hierarchical mixed effects logistic regression framework, to estimate the odds of: 1) skilled birth attendance (SBA), 2) receiving 4+ antenatal care (ANC) visits, and 3) receiving a postnatal health check-up (PNC) within 48 hours of delivery. Model results are applied to an accessibility surface to visualise the probabilities of obtaining MNH care at both high-resolution and sub-national levels after adjusting for live births in 2015. Across all outcomes, decreasing wealth and education levels are associated with lower odds of obtaining MNH care, while increasing geographic inaccessibility scores are associated with the strongest effect in lowering odds of obtaining care observed across outcomes, with the widest disparities observed among skilled birth attendance.

The second paper explores temporal trends in absolute and relative spatial inequalities in utilisation of these MNH services between 1990 and 2015. A Bayesian framework is employed to generate sub-national estimates of utilisation of SBA, ANC, and PNC over several time points. Absolute change in estimates over time is reported, as well as relative change in ratios of the best-to-worst performing districts per country. Across all countries, the greatest spatial equality is observed among ANC, while SBA and PNC tend to have greater spatial variability. Lastly, while progress has been made to reduce coverage gaps between districts, improvement in PNC coverage has stagnated and should be monitored closely over the coming decades.

The final paper comprising this work explores the trade-off between increasing spatial resolution in model inputs and resulting model uncertainty, with aims of understanding the optimal spatial resolution to report health outcomes. Prevalence of childbirth via c-section is estimated in Tanzania, using geospatial covariates at varying levels of spatial coarseness within a Bayesian model framework. Uncertainty in posterior outcomes is reported as the distribution of 95% credible intervals at each spatial resolution, and visualised at the spatial resolution with the greatest model precision. Overall, higher spatial resolution input increases model uncertainty, while model precision is best approximated at the highest spatial resolution, suggesting an important policy trade-off between identifying concealed spatial heterogeneities in health indicators.

This thesis makes substantive contributions to the literature by outlining where spatial inequalities in key MNH services are occurring within the EAC region and how these disparities are evolving over time. This work also makes methodological contributions by demonstrating how spatial approaches can be used to monitor health indicators, as well as exploring uncertainty in the application of these techniques, with important implications in communicating results to policy makers. These techniques can be applied across health and development outcomes, notably across Sustainable Development Goal indictors, ensuring "no one left behind" by 2030.

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Research Thesis: Declaration of Authorship

Print name:	Corrine Warren Ruktanonchai
Title of thesis:	Mapping Spatial and Temporal Inequalities in Utilisation of Maternal and Newborn Care in Five East African Countries

I declare that this thesis and the work presented in it are my own and has been generated by me as the result of my own original research.

I confirm that:

1. This work was done wholly or mainly while in candidature for a research degree at this University;
2. Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated;
3. Where I have consulted the published work of others, this is always clearly attributed;
4. Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work;
5. I have acknowledged all main sources of help;
6. Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself;
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Signature: Date:

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Definitions and Abbreviations

AIS	AIDS Indicator Surveys
AMDD	Averting Maternal Death and Disability
ANC	Antenatal care
CI	Confidence/credible interval
DHS	Demographic and Health Surveys
DIC	Deviance Information Criterion
EAC	East African Community
EmOC	Emergency obstetric care
EPMM	Ending Preventable Maternal Mortality
GIS	Geographic information system
GPS	Global positioning system
HMIS	Health management information systems
INLA	Integrated Nested Laplace Approximation
SBA	Skilled birth attendance
SSA	Sub-Saharan Africa
MDG	Millennium Development Goals
MIS	Malaria Indicator Surveys
MMR	Maternal mortality ratio
MNH	Maternal and newborn health
OR	Odds ratio
PMNCH	Partnership for Maternal, Newborn and Child Health
PNC	Postnatal care
RMNCAH	Reproductive, maternal, newborn, child, and adolescent health

SAE	Small area estimation
SD	Standard deviation
SDG	Sustainable Development Goals
SPA	Service Provision Assessment
SPDE	Stochastic partial differential equation
UN	United Nations
UNICEF	United Nations International Children’s Emergency Fund
UNFPA	United Nations Fund for Population Activities
WHO	World Health Organization

Chapter 1: Introduction

1.1 Background

With the establishment of the Millennium Development Goals (MDGs) in 2000, maternal mortality was nearly halved worldwide by the year 2015, while under-5 mortality was reduced by over 50%, from 90 to 43 deaths per 1,000 livebirths (United Nations, 2015a). Despite this progress, movement towards maternal and child health MDG targets stubbornly lagged behind, with many countries failing to achieve a reduction of under-5 mortality by two-thirds (MDG 4) and maternal mortality by three-quarters (MDG 5). In 2015, the United Nations (UN) renewed their call for action with the establishment of the Sustainable Development Goals (SDGs), aimed at ensuring no one left behind and that future progress in improving health is seen among all populations among all countries. Particular attention has been placed on monitoring progress both within and between countries in order to close health inequalities amongst the most vulnerable (United Nations General Assembly, 2015). Towards this, sub-national monitoring of health disparities within countries has been emphasised to better ensure sustainable progress is achieved by the year 2030, in addition to better stakeholder engagement and capacity strengthening.

As the world moves further into the post-2015 SDG era, however, health inequalities continue to persist among the world's most vulnerable populations (United Nations General Assembly, 2015). Pregnant women, newborns and children remain particularly at risk, and while progress has been made in reducing the total number of women dying in childbirth, the global maternal mortality ratio in 2015 was estimated at 216 deaths per 100,000 live births (WHO et al., 2015). A further 19 newborns per 1,000 live births were estimated to have died within the first 28 days of life in 2015 (UN Inter-agency Group for Child Mortality Estimation, 2015; WHO et al., 2015). These deaths occur predominantly in low resource settings, and the vast majority can be prevented (Alkema et al., 2016a).

The UN has consequently renewed its call for action in preventing these deaths, with ambitious SDG targets of reducing the global maternal mortality ratio to less than 70 per 100,000 live births and neonatal mortality rate to under 12 per 1,000 live births (United Nations General Assembly, 2015). Yet Boldosser-Boesch and colleagues from the Ending Preventable Maternal Mortality (EPMM) work group argue that in addition to this global maternal mortality ratio target, national level targets are also critical in accelerating reduction of maternal mortality by the 2030 timeframe (Boldosser-Boesch et al., 2017). Specifically, the EPMM recommended country targets to increase equity in maternal mortality, where: 1) countries with a baseline MMR in the year 2010 of less than 420 per 100,000 live births should reduce MMR by two-thirds by the year 2030; 2) countries with an MMR in 2010 of greater than 420 per 100,000 live births should not have an MMR greater than twice that of the global target (or 140) by 2030; and, 3) countries with a baseline MMR in 2010 of less than 10 per 100,000 should aim to achieve equity in MMR at the sub-national level (WHO and HRP, 2015).

These national level estimates, however, represent a historical push to monitor progress in maternal and newborn health (MNH) outcomes at aggregate levels such as the national and multi-national level, and themselves show vast inequality between countries (Bhutta ZA and Reddy K, 2012). Examining inequality indices among 12 key MNH intervention indicators, Barros and colleagues found substantial variation in coverage of interventions between over 50 countries that account for nearly 95% of all maternal, newborn and child deaths (Barros et al., 2012; Bhutta ZA and Reddy K, 2012). These inequality measures varied not only between countries, but within country, as well, with the most disparities observed among skilled birth attendance at delivery, followed by 4+ antenatal care visits prior to delivery (Barros et al., 2012). These findings suggest that even among countries with improved national-level outcomes, aggregated measures of health may mask local, worsening inequalities among already marginalized and vulnerable populations, such as the poorest and most remote (Bhutta ZA and Reddy K, 2012; Ebener et al., 2015). In order to therefore ensure sustainable and measureable progress amongst all, policymakers have increasingly called for the spatial and temporal disaggregation of MNH data, as evidenced by the recent emphasis on sub-national monitoring within the SDGs (United Nations General Assembly, 2015; WHO, 2015a).

Researchers have heeded this call, and recent literature reviews such as those performed by Makanga and colleagues and Ebener et al. suggest that evidence exploring access to healthcare within an explicitly spatial context is emerging (Ebener et al., 2015; Makanga et al., 2016). Both reviews, however, note that a need remains to apply a geographic framework using a more nuanced and spatially explicit approach, helping to account for variation in MNH indicators and outcomes within the context of geography. Specifically, while Ebener et al. note a substantial increase in the number of studies utilising geographical methods to study MNH indicators since 2010, both reviews found that a large majority of spatial research done within an MNH framework has focused predominantly on quantifying geographic access to health facilities (Ebener et al., 2015). This is in line with Makanga et al., who note that a spatially explicit approach quantifying access to health services is a shared theme among other studies. Despite this, they argue a lack of evidence exists correlating these modelled accessibility measures to observed individual-level MNH outcomes, as well as facility-level indicators such as intervention coverage and quality of care indicators (Makanga et al., 2016).

Yet ensuring SDG targets are achieved necessitates not only an increase in spatial disaggregation of data, but also temporal disaggregation to monitor progress (United Nations General Assembly, 2015; WHO, 2015a). By monitoring spatially disaggregated data over time, progress within and between subgroups can be assessed over two or more time points (WHO, 2015a). Temporal disaggregation of data and comparison between those time points present a unique set of complications, however, as outlined by Barros and Victora (Barros and Victora, 2013). Addressing these complications, they argue that both absolute and relative measures of temporal inequalities should be reported, as these measures can particularly interact and mask increasing or decreasing inequalities over time. For example, Minujin and Delamonica report relative trends over time in under-5 mortality rates among the poorest and richest quintiles within 24 countries (Minujin and Delamonica, 2003). Specifically, they found differentials between the highest and lowest wealth quintiles actually increased over the span of a decade, driven by a reduction in mortality observed among the middle quintiles. These findings suggest that inequalities between the poorest and richest may actually be widening, despite an overall reduction in mortality over time.

Boerma et al. similarly explored coverage of key MNH interventions among the countries most vulnerable to adverse MNH outcomes, as identified in the Countdown to 2015 for Maternal, Newborn and Child Survival initiative (Boerma et al., 2008). Similar to previous studies, they observed wide gaps both between and within countries, but further noted these inequalities persisted throughout time with little to no change, particularly between the poorest and richest quintiles. Lastly, Nguhiu and colleagues examined the change in effective coverage of maternal and child health services over time within Kenya, an aggregate level indicator incorporating information on quality of care, health systems performance, and service use. They similarly found that while effective coverage had steadily increased over time, inequalities in particular services persisted, namely among antenatal care, skilled birth attendance and family planning (Nguhiu et al., 2017). Such consensus suggests that aggregate level targets may not be adequate in ensuring that the most vulnerable sub-populations of a country will see the same improvement observed at a national level, and monitoring progress among these groups over the coming decades will therefore be key to achieving the targets laid out by the SDGs.

The use of Geographic Information Systems (GIS) as a tool to achieve spatial and temporal disaggregation of data and highlight vulnerable populations is becoming increasingly recognized, particularly within the field of MNH (Ebener et al., 2015; Makanga et al., 2016). In an outline of the current state of the geography of MNH, Ebener and colleagues broadly categorized the published use of GIS methodology into three themes in increasing order of complexity: 1) thematic mapping (creation of basic maps to convey a topic or theme), 2) spatial analyses (creation or extraction of new information from spatial data), and 3) spatial modelling (spatial analysis with the use of mathematical or statistical models to simulate real-world phenomena) (Ebener et al., 2015). Similarly, Makanga et al. noted two major themes in the use of GIS in maternal care: modelling access to health services and analysis of risk factors associated with adverse maternal health outcomes (Makanga et al., 2016).

While the historic use of GIS within health literature was limited until more recent decades (Boulos, 2004; Higgs, 2004), the availability of newly disaggregated geographic data and advanced computational infrastructure have allowed greater application of GIS methodologies and tools to health research (Auchincloss et al., 2012; Musa et al., 2013), as evidenced by the establishment of academic journals such as *International Journal of Health Geographics* (2002) and *Spatial and Spatio-Temporal Epidemiology* (2009), among others. These methods can help fill knowledge gaps for health geographers and epidemiologists, guide policy discussions and intervention efforts in a comprehensive framework and ensure adequate attention to marginalized populations (Boulos, 2004; Goldenberg and McClure, 2012; Higgs, 2004; Makanga et al., 2016; Musa et al., 2013; Nykiforuk and Flaman, 2009). However, the application of GIS in addressing maternal health research has faced unique challenges, as outlined by Molla and colleagues (Molla et al., 2017). These challenges broadly included: limited high quality, geo-referenced MNH data at sufficient spatial resolutions to allow spatial analysis at policy-relevant geographic units (e.g., vital registration statistics, including births and maternal deaths); limited technical expertise, institutional capacity and human resource availability to conduct analyses within low and middle income countries; and, a lack of community participation and participatory approaches including key MNH workers such as community health workers and nurses.

1.1.1 Global initiatives in maternal and newborn health

The UN Millennium Summit in 2000 set the global stage for monitoring and reducing maternal and child mortality, with specific targets to reduce under-5 mortality by two-thirds and maternal mortality by three-quarters by the year 2015 (United Nations, 2015a). The Countdown to 2015 for Maternal, Newborn, and Child Survival was established shortly thereafter in 2005 to ensure accountability for achieving these targets among the 75 most vulnerable countries (the ‘Countdown countries’) accounting for over 95% of global maternal and child mortality (UNICEF and WHO, 2015). Towards this, the Countdown initiative monitored progress among key maternal, newborn and child mortality interventions within and between countries, identifying key gaps in both intervention coverage and data since 1990. Specifically, priorities of the initiative as outlined by Bhutta and colleagues included:

1) selection and monitoring of evidence-based key interventions proven to reduce maternal, newborn and child mortality;
2) production of key country profiles to support policy guidance and decision making;
3) tracking progress towards MDGs 4 and 5;
4) recommendations on action to promote equitable coverage of key interventions;
5) ensuring accountability from both national governments and the international development community to ensure MDG targets are met; and,
6) identifying gaps in knowledge and implementation which are hindering progress towards meeting these goals (Bhutta et al., 2010).

As the MDGs reached their conclusion in 2015, Victora and colleagues assessed global progress among these 75 Countdown countries to take stock of progress and lessons learned, as well as identify next steps (Victora et al., 2016). Overall, they found that the global maternal mortality ratio decreased by 45% over the span of two decades from 380 maternal deaths per 100,000 live births to 210, with the most progress achieved between 2000 and 2013 (United Nations, 2015a). Globally, Southern and Eastern Asia saw the greatest progress in reducing maternal mortality, down 64% and 65%, respectively. Despite this accelerated progress, many countries failed to achieve the MDG 5 target of reduction in maternal mortality ratio by three quarters. These failures were largely a result of causes which could have been prevented through basic and essential intervention packages as outlined by the Partnership for Maternal, Newborn & Child Health (PMNCH), ensuring adequate provision of services throughout pregnancy, birth and the postpartum period (PMNCH, 2011; Say et al., 2014a). Indeed, among these 75 countries, Victora and colleagues note only four countries met targets for both MDGs 4 and 5 (Cambodia, Eritrea, Nepal, and Rwanda).

Although only a small minority of countries met the specified targets outlined by MDGs 4 and 5, the Countdown initiative found that coverage increased for most interventions that are known to combat maternal and child deaths, such as skilled birth attendance, antenatal and postnatal care, and vaccination coverage amongst both women and children. They further found that coverage gaps between the richest and poorest quintiles in 47 countries narrowed among eight key interventions outlined by the WHO in reducing maternal and child deaths (UNICEF and WHO, 2015; Victora et al., 2016). In addition to coverage, financing for maternal, child and newborn health increased and many countries adopted more MNCH friendly policies. Yet regardless of this progress, many disparities (largely socioeconomic) continued to persist in nearly every Countdown country, both in terms of intervention coverage and resources, as well as financing and policies. Further, coverage of these interventions varied substantially between countries in addition to within country variation (UNICEF and WHO, 2015). Finally, the Countdown initiative also noted problems faced by data availability, and the research community's subsequent overall dependence on modelled mortality estimates. They therefore recommended development of innovative measurement techniques as the world moved into the SDG era, with particular emphasis on equity and sub-national monitoring of social and environmental determinants and their impact on health (Victora et al., 2016).

Moving forward, the UN has defined a global MMR target of less than 70 maternal deaths per 100,000 live births by the year 2030. Contention exists, however, as to what global agenda over the coming decades is best suited to not only reach this target, but also ensure equitable progress is seen among the most vulnerable populations (Boldosser-Boesch et al., 2017). Towards this, the UN Secretary-General launched a Global Strategy for ensuring the health and rights of women, children and adolescents, with key connections to the Every Woman Every Child initiative launched in mid-2015. Together, these frameworks aimed to outline a clear roadmap to ending preventable maternal deaths, newborn and child deaths, while promoting human rights and equitable progress (United

Nations, 2016). To accomplish this, the Ending Preventable Maternal Mortality (EPMM) and Every Newborn Action Plant (ENAP) working groups through the World Health Organization (WHO) were created with a grounding in human rights principles. These groups aim to end preventable maternal and neonatal deaths through elimination of disparities in access to and utilisation of care across the reproductive life course (WHO, 2014; WHO and HRP, 2015). In addition to SDG targets of less than 70 maternal deaths per 100,000 live births, EPMM further outlined that no country should have an MMR greater than 140, while ENAP set targets of less than 10 newborn deaths per 1,000 live births by the year 2035.

1.1.2 Maternal and newborn health in sub-Saharan Africa

With almost two-thirds of Countdown countries falling in the African continent, sub-Saharan Africa (SSA) saw a nearly 50% reduction in maternal mortality since 1990 (United Nations, 2015a). Despite this progress, this region accounts for the highest regional maternal mortality ratio in the world, at just over 500 maternal deaths per 100,000 live births in 2013, compared to a global rate of 210 deaths. Further, only four countries achieved the 75% reduction set out by MDG 5 (United Nations, 2015a). Together with Southern Asia, maternal deaths in SSA account for 86% of global maternal deaths, with over half due to causes such as haemorrhage (25%), hypertensive disorders (16%) and sepsis (10%) (Say et al., 2014a). By increasing access and equitable coverage of quality care including antenatal and postnatal care and skilled birth attendance, these deaths could be prevented (UNICEF and WHO, 2015; United Nations, 2015a).

Encouragingly, the global proportion of births attended by skilled personnel increased, and in many parts of the world such as Central and Eastern Asia and the Americas the proportion of deliveries attended by skilled birth attendants in 2013 reached well over 90% (Say et al., 2014a; UNICEF and WHO, 2015). In SSA, however, the increase in proportions of births attended by skilled personnel was more modest and still represents some of the lowest proportions globally, with nearly half of babies delivered without skilled care (United Nations, 2015a, 2015b). Further, the coverage of skilled attendance at delivery was inequitably distributed across regions, with the greatest inequalities observed in Central Africa at only 32% skilled attendance in rural areas as compared to 84% in urban (United Nations, 2015a). Similar to skilled attendance at delivery, only half of pregnant women receive the recommended number of four antenatal care visits, and SSA represented the least amount of change regionally with only 2% increase between 1990 and 2014 (United Nations, 2015a). These gaps suggest that even though global progress has been made in reducing maternal mortality, these advances may mask sub-national and regional health disparities. These disparities are driven by inequalities in intervention coverage which continue to persist, and are disproportionately impacting vulnerable women who need these services the most (United Nations, 2015a).

1.2 Study objectives

As the development world moves away from the MDGs into the SDG era, disaggregated spatial and temporal data are needed along which to monitor change and measure progress the development world is to ensure that new global targets are achieved by the year 2030. This is particularly relevant in resource-poor countries with disproportionately high burdens of maternal and child deaths, such as countries falling within the SSA region. The objective of this thesis is to address this need within several African countries by generating high-resolution data that can be used to monitor spatial and temporal change, with specific aims to:

1) Produce estimates of the probability of utilising MNH services as predicted by geographic accessibility at both high spatial resolution and policy relevant scales, highlighting spatial heterogeneity and sub-national inequalities;

2) Track how spatial inequalities in utilisation of MNH services have changed over time, identifying sub-national regions which have made progress in narrowing inequalities over time, as well as regions where progress still needs to be made; and,

3) Quantify the trade-off between increasing spatial resolution of modelled estimates of delivery via caesarean section in Tanzania, and associated uncertainty in model outcomes.

This work follows a “three-paper PhD” structure and is therefore be organized to address the above aims, with chapters 4 through 6 following traditional journal article format. Chapter 1 includes a broad introduction to the global and regional epidemiology of maternal and newborn health, including overall study objectives of this thesis. Chapter 2 consists of a substantive literature review outlining the fields of maternal and newborn health and spatial demographic data for health, while Chapter 3 outlines the study framework, including study indicators, study area, research questions and study methods used. Chapter 3 concludes with how this work contributes to the current literature as well as intellectual contribution for each analytic chapter, and finally how this work generates broader impact. Chapter 4 consists of an expanded version of the article, “Equality in Maternal and Newborn Health: Modelling Geographic Disparities in Utilisation of Care in Five East African Countries”, as published in PLoS ONE’s special collection, *Neglected Populations: Decreasing Inequalities & Improving Measurement in Maternal Health* (C. W. Ruktanonchai et al., 2016). Chapter 5 explores the temporal evolution of spatial inequalities in MNH services within the East Africa Community, “Temporal trends in spatial inequalities of maternal and newborn outcomes among four East African countries, 1999 – 2015”, as published in BMC Public Health (C. W. Ruktanonchai et al., 2018). Chapter 6 explores the trade-off between increasing spatial resolution in model inputs and associated model outcomes and measures of uncertainty among delivery via caesarean section in Tanzania, titled “Estimating uncertainty in geospatial modelling at multiple spatial resolutions: the pattern of delivery via caesarean section in Tanzania”, as accepted to BMJ Global Health. Finally, Chapter 7 includes a synthesis of substantive and methodological findings and broad conclusions from the preceding chapters, with aims of outlining academic and policy impact generated from this work as well as broad policy recommendations, where appropriate.

Chapter 2: Literature Review

To address the objectives of this thesis, a detailed understanding of how, why and where maternal and newborn deaths and complications are occurring is needed, as well as what health services can prevent these deaths. To answer these questions within a geographic framework, this chapter first explores causes of maternal and newborn deaths, what health services are recommended to encourage healthy pregnancy and childbirth, and barriers to obtaining these services within predominantly resource-poor settings. Next, a synthesis of the current framework for monitoring progress of maternal and newborn health within the SDG era is outlined, followed by how, where and to whom spatial and temporal health inequalities occur, as well as previous methods for measuring inequalities in space and time. The role of spatial demographic data in improving maternal and newborn health is then discussed, with a synthesis of existing spatial data within the study region, as well as where knowledge gaps still exist.

The purpose of this chapter is two-fold: firstly, to synthesize the extant literature on the above topics to identify knowledge gaps; and secondly, to provide a theoretical foundation for the remaining chapters of this work (Paré and Kitsiou, 2017). This chapter therefore represents a qualitative narrative review of the existing literature (Sylvester et al., 2013), and while no structured or standardised approach was employed to exhaustively search the literature, a 'snowball' methodology was generally employed wherein relevant citations and additional references were identified within pertinent pieces of work, such as review articles and meta-analyses (Wohlin, 2014).

2.1 Maternal and newborn health

Pregnancy and childbirth should be a time of joy and empowerment for all women, but in many countries across the world, this period can pose critical health risks and complications which too often prove fatal for either the woman, newborn, or both. The health of a woman and her newborn child are inextricably linked, and addressing the health concerns of one inevitably impacts the other. The complications arising out of pregnancy, labour and childbirth, however, vary for woman and child, and resulting fatalities can be caused by vastly different reasons. This section therefore explores the causes of deaths for women and newborns separately, followed with what services are recommended for the health of women and children, plus common barriers associated with obtaining those services on both the supply and demand side. This section concludes with a synthesis of progress in monitoring and evaluation in the field of maternal and newborn health, and outlines the current state of inequalities in maternal and newborn health across the globe.

2.1.1 Causes of maternal death

To achieve global development targets outlined by the SDGs, a clear and nuanced understanding of the causes of maternal and newborn deaths worldwide is needed. The WHO has defined maternal deaths as deaths occurring among pregnant women, or within 42 days of termination of pregnancy (either via delivery or other means), attributed to any cause related to pregnancy, delivery, or its management, excluding incidental or accidental causes (WHO et al., 2015). This definition allows for identification of both direct and indirect causes of maternal deaths, provided routine health records are captured. In reality, however, such routine data is rarely captured amongst the most vulnerable women, particularly in countries with the highest rates of maternal mortality (Say et al., 2014a). Therefore, systematic analyses have been necessary over the decades to adequately report and monitor both direct and indirect causes of maternal mortality.

Analysing 34 datasets representing over 35,000 maternal deaths across various geographic regions throughout the world, Khan et al. describe primary causes of maternal deaths (Khan et al., 2006). Globally, they attributed the leading causes of deaths to haemorrhage and hypertensive disorders, yet they found leading causes of death varied across regions. While progress has been made in reducing the overall number of maternal deaths since 1990, Requejo and Bhutta note that more than half of women who die from complications due to pregnancy are dying from severe bleeding, hypertension and sepsis (Figure 2.1), which can be alleviated through skilled birth attendance and timely postnatal care check-ups (Requejo and Bhutta, 2015).

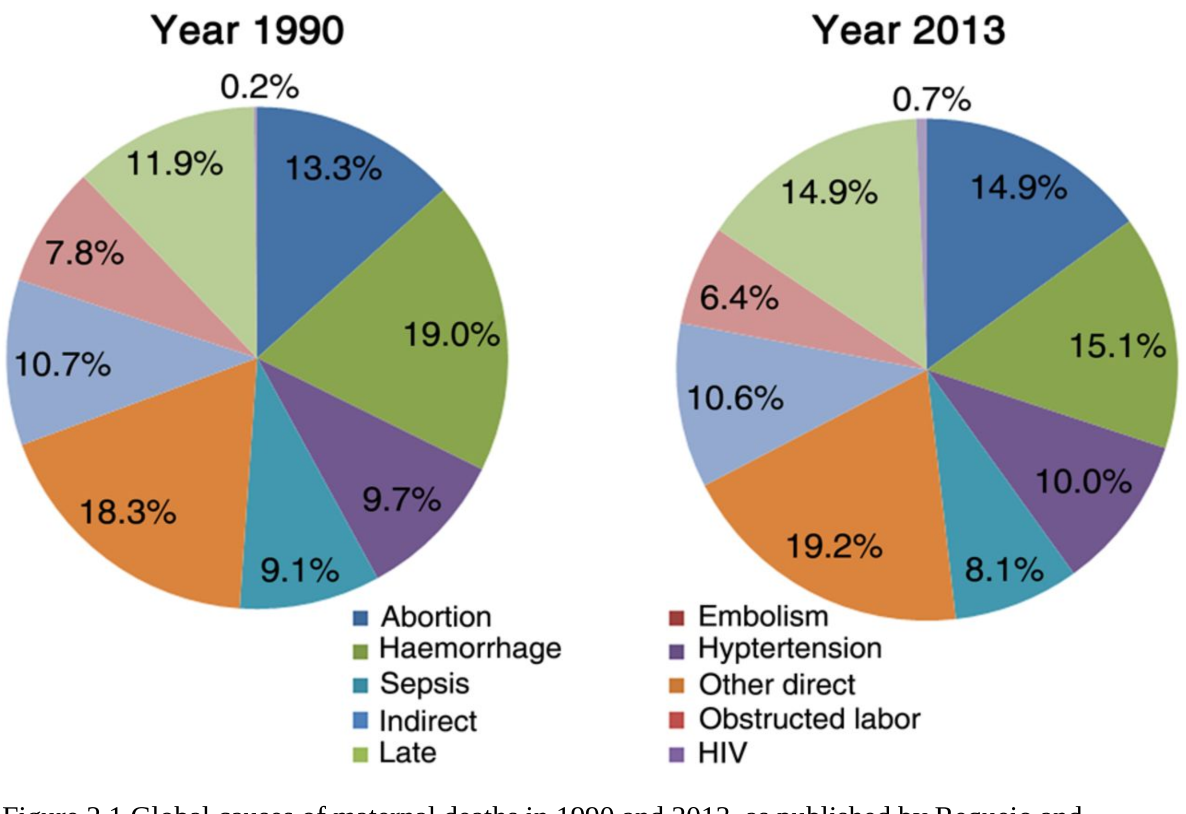


Figure 2.1 Global causes of maternal deaths in 1990 and 2013, as published by Requejo and Bhutta, 2015

Khan et al. found these trends also occurred regionally—within Africa and Asia, the leading cause of death was haemorrhage, accounting for 33.9% of deaths in Africa (CI 13.3% - 43.6%) and 30.8% of deaths in Asia (CI 5.9% - 48.5%). Alternatively, within Latin American and Caribbean countries, hypertensive disorders accounted for over a quarter of deaths (25.7%, CI 7.9% - 52.4%). Lastly, deaths due to abortions were noted to be particularly high in some Latin American countries, while deaths due to sepsis were higher among study countries as compared to developed countries (Figure 2.2) (Khan et al., 2006).

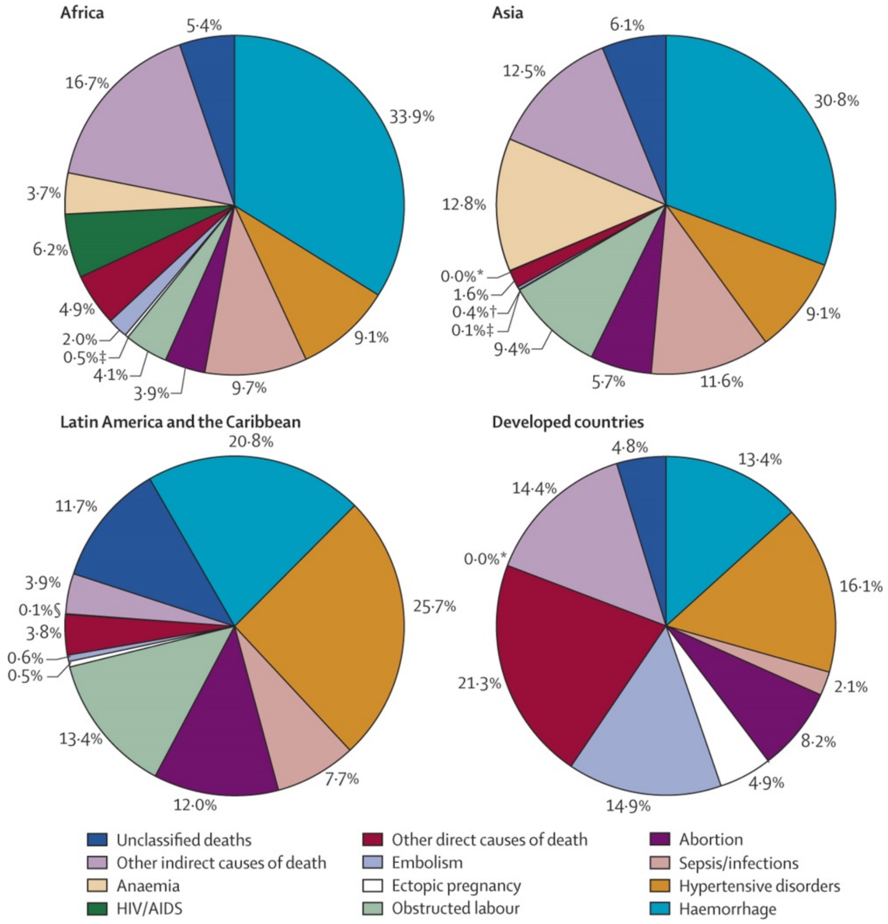


Figure 2.2 Distribution of causes of maternal deaths by WHO geographical region, as published by Khan et al., 2006

Following similar methodology as Khan et al., Say and colleagues followed up with another systematic analysis of maternal deaths in 2014. Using 417 datasets comprising 115 countries, they examined nearly 61,000 maternal deaths between 2003 and 2009 (Say et al., 2014a). Globally, they similarly found that haemorrhage, hypertensive disorders and sepsis were the leading causes of maternal deaths, accounting for more than half of maternal deaths worldwide. They also noted that indirect causes of deaths, such as medical disorders and HIV-related maternal deaths, could be attributed to nearly a quarter of deaths worldwide (Say et al., 2014a).

The majority of complications discussed above arise during labour, delivery and the immediate post-partum period—however, the majority of deaths occurring from these complications can be prevented, provided immediate and appropriate medical care (Alkema et al., 2016a). Why, then, do these deaths continue to occur, despite progress in reducing mortality over the previous decades? Thaddeus and Maine proposed a seminal framework to contextualize these maternal deaths in low and middle-income countries, and explain why preventable fatalities continue to occur (Thaddeus and Maine, 1994). Specifically, they focus on the critical period of risk for a woman between the onset of labour and delivery, proposing that adequate treatment or care provided within this interval will usually result in a positive outcome, whether a complication has arisen or not. Many deaths are therefore preventable through provision of treatment, but often the decision to seek or obtain this care can be fraught with life-threatening delays. They subdivide these barriers into a three-delay framework: 1) the decision to seek care, 2) arrival at a care facility, and 3) the provision of care after arrival at a care facility. At each stage of these decisions, barriers and delays may be experienced, resulting in continuation of life-threatening complications or death. Maternal mortality prevention programs must therefore contextualize each of these delays within any intervention effort, in order to effectively treat labour and delivery complications and ultimately reduce preventable maternal deaths (Thaddeus and Maine, 1994).

2.1.2 Causes of newborn deaths

The MDGs established in 2000 aimed to reduce not only maternal mortality by three-quarters, but also under-five child mortality by two-thirds. Among children dying under the age of 5 years old, the largest proportion of deaths have historically been comprised of neonates, or those between 0 – 27 days old (Black et al., 2010; Liu et al., 2015, 2012; Rajaratnam et al., 2010). Globally, neonatal deaths declined 2.1% per year and were nearly halved between 1970 through 2010, with similar patterns of accelerating reductions post-2000 (as compared to 1990 – 2000). The most progress was seen in the Western Pacific and Europe, while the least progress seen in Africa and the Eastern Mediterranean (Liu et al., 2012). Yet despite global progress in reducing child mortality, 3.1 million neonatal deaths continued to occur in 2010, comprising over 40% of global under-five mortality (Rajaratnam et al., 2010). Requejo and Bhutta also note that the number of deaths occurring within the first 4 weeks of life are in fact a growing proportion of under-5 mortality (Figure 2.3), and that progress in reducing neonatal mortality specifically, is lagging globally (Requejo and Bhutta, 2015). These findings echoed results published by Liu and colleagues, showing that global trends in the reduction of neonatal deaths have remained relatively consistent since 2000, especially as compared to other causes of under-5 mortality such as diarrhoeal diseases and measles, as shown in Figure 2.4 (Liu et al., 2012).

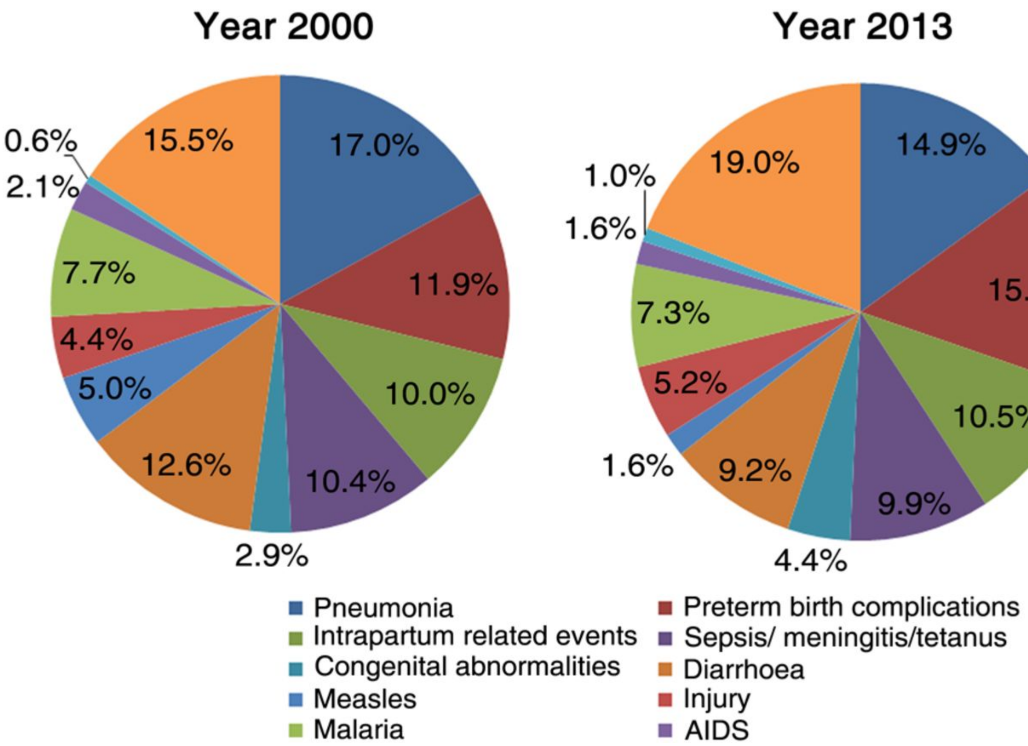


Figure 2.3 Global causes of under-5 mortality in 2000 and 2013, as published by Requejo and Bhutta, 2015

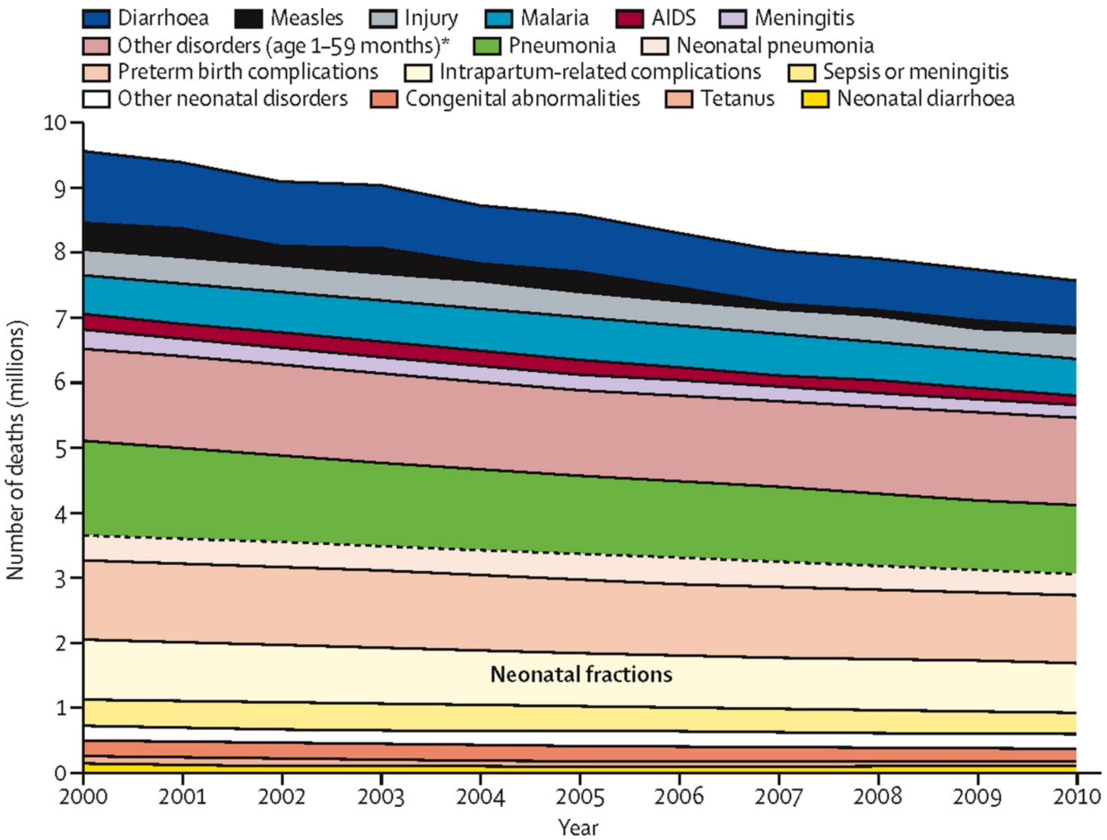


Figure 2.4 Global trends in under-5 childhood mortality in 2000 - 2010, as published by Liu et al., 2012

The systematic analysis conducted by Liu et al. in 2012 explored global, regional and national causes of deaths among under-fives, and found in 2010 that the leading causes of neonatal deaths included preterm birth and intrapartum-related complications, sepsis or meningitis, and pneumonia (Figure 2.5) (Liu et al., 2012). These findings were echoed by Black and colleagues, who found leading causes of neonatal deaths were attributed to preterm birth complications, birth asphyxia and sepsis in 2008 (Black et al., 2010). Further, neonatal deaths comprised high proportions of under-five mortality (ranging from 48% to 54%) in the Americas, Southeast Asia, the Western Pacific and Europe, with leading causes of death attributed to preterm birth complications and birth asphyxia. Lastly, Africa and Southeast Asia saw the greatest number of total under-five deaths at 4.199 million and 2.390 million deaths, respectively (Black et al., 2010).

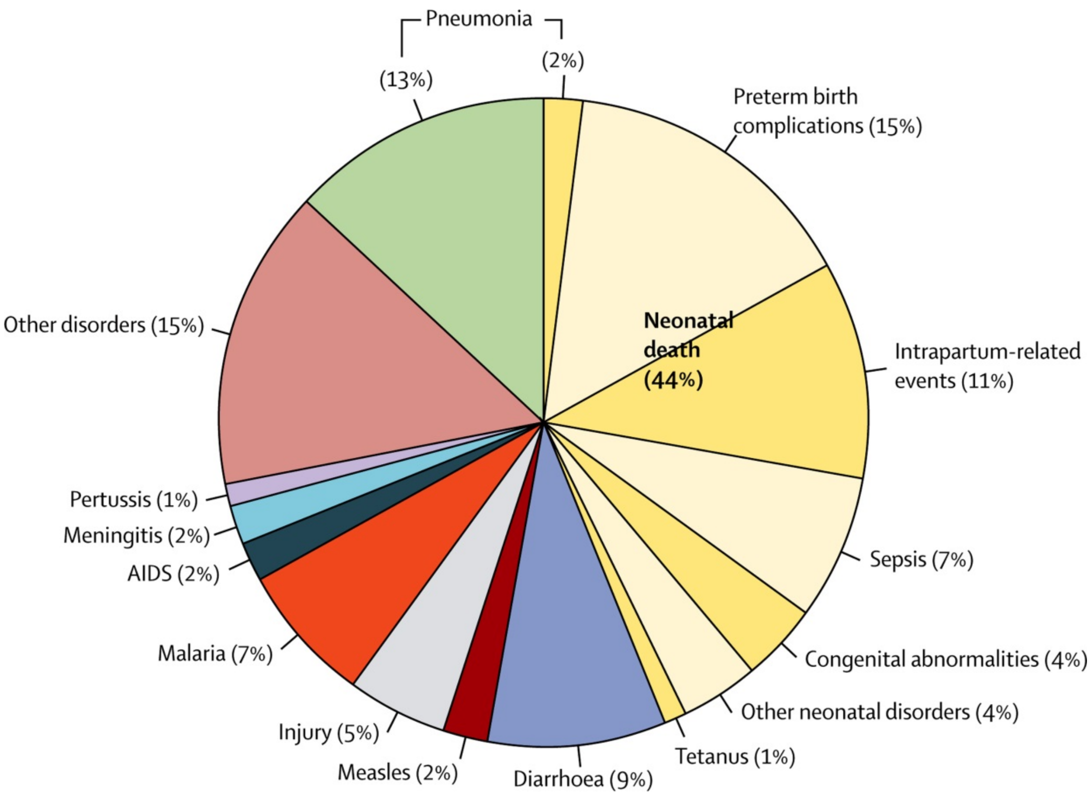


Figure 2.5 Global causes of under-5 mortality, separated into neonatal deaths (0 - 27 days) and deaths among children aged 1-59 months, as published by Liu et al., 2014

Performing a follow-up systematic analysis five years later, Liu and colleagues later found similar results globally among leading causes of death among neonates, with preterm birth and intrapartum-related complications representing the leading causes, followed by sepsis and congenital abnormalities. Notably, neonatal tetanus, diarrhoea and pneumonia represented substantial yearly reductions from 2000 – 2013, at 8.9%, 6.0% and 5.2% annual reductions, respectively. The majority of reductions in under-five deaths have, however, been largely isolated to deaths among children aged 1-59 months, with little decline seen among those in the first 27 days of life (Figure 2.4). Lastly, they outline that if present trends continued, sub-Saharan Africa will account for a disproportionately high rate of under-five deaths as compared to births, estimating it will account for 33% of global births in 2030, yet 60% of under-five deaths (Liu et al., 2015).

2.1.3 Maternal and newborn health services

Preventing the deaths of women and newborns ultimately requires delivery of timely and high quality service packages and interventions across the continuum of care (Kerber et al., 2007). Many definitions of ‘continuum of care’ exist, but the WHO notes that ‘continuum of care’ is two-pronged, occurring over both time and space. This firstly means care is provided throughout the life course, spanning the neonatal period to adolescence to reproductive years through pregnancy, and secondly means that care is provided seamlessly, spanning “the home, the community, the health centre and the hospital” (WHO, 2005). Kerber et al. build upon this definition, arguing that prevention of lives is dependent upon functional linkages of services and health care systems across the reproductive life course, resulting in care that “contributes to the effectiveness of all the linked packages” (Kerber et al., 2007).

Countries with the highest levels of maternal and neonatal deaths often also tend to be limited in resources, such as health personnel, funds and supplies. Given these limitations, studies have suggested that essential health intervention packages exist which could avert up to 67% of neonatal deaths within the most vulnerable countries worldwide (Kerber et al., 2007). Kerber and colleagues outlined eight such essential packages across the continuum of care, grouped into services provided through clinical care, outpatient and outreach services, and family and community care. Within these provisional groupings, services were further categorised along the continuum of care, as defined in Figure 2.6.

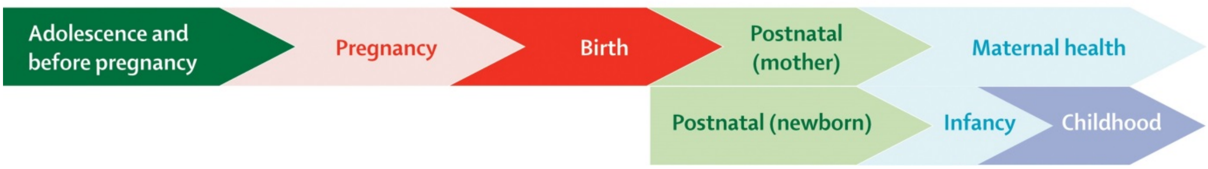


Figure 2.6 The reproductive life course across which care packages must be integrated, adapted from Kerber et al., 2007

Across the spectrum of pregnancy, childbirth, and the immediate postnatal period, the most life-threatening conditions can occur suddenly and without warning, and require timely and high quality management. Victora et al. identified critical services across the continuum of care which are crucial in determining the survival of women, newborns, or both (Figure 2.7) (Victora et al., 2016).

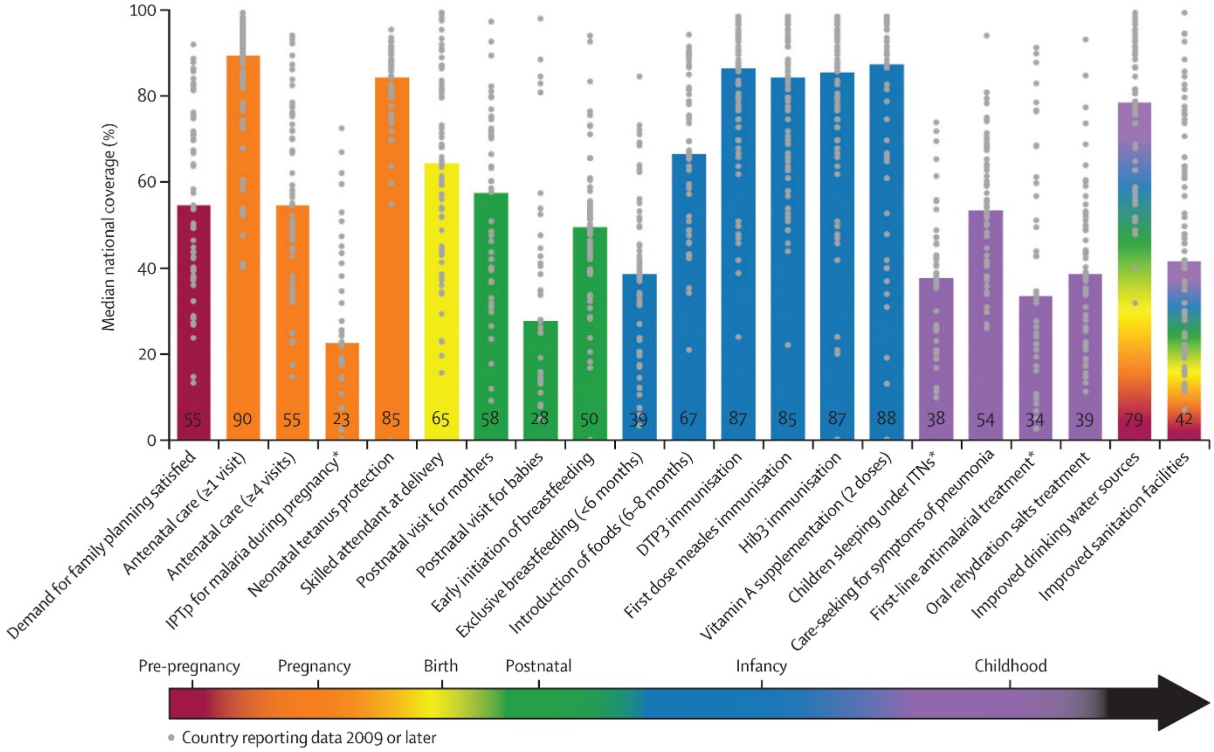


Figure 2.7 Median coverage of interventions among Countdown countries, across the continuum of care, as published by Victora et al, 2016

Nyamtema and colleagues further performed a systematic review of health interventions which were most likely to have positive impacts on maternal health outcomes, specifically within limited resource settings (Nyamtema et al., 2011). Out of nearly 60 publications, they found no single intervention alone was sufficient in reducing maternal mortality, reiterating integration of multiple service packages were most effective in influencing health outcomes. Generally, however, they found that the most impactful interventions focused on increasing functional access and delivery of skilled birth attendance with sufficient equipment, such as supplies, drugs and referrals to higher-level health care systems in the event of complications. Other services key to ensuring healthy delivery for both the woman and child also included four or more antenatal care visits (focused on malaria prevention, provision of insecticide-treated bed nets, and other preventative treatments), and postnatal care for both woman and newborn in the hours after delivery.

Even with high coverage of essential interventions such as skilled birth attendance and adequate antenatal care, maternal mortality may not be substantially reduced without equally high coverage of comprehensive emergency care (Souza et al., 2013). Globally, nearly 75% of maternal deaths were caused by obstetric complications between 2003 and 2009, with haemorrhage and hypertension as the leading causes of death (Say et al., 2014a). Access to readily available emergency obstetric care (EmOC) services where life-threatening obstetric complications can be quickly identified and readily treated are therefore key in preventing maternal deaths (Paxton et al., 2005). To combat these preventable deaths, UNICEF, WHO, and the UNFPA, outlined a baseline package of services that health facilities should offer, aimed at treating the 7 major direct causes of obstetric complications leading to death, collectively known as emergency obstetric care (EmOC) (UNICEF et al., 1997).

To quantify the availability of these medical interventions and to measure progress in reducing maternal and perinatal deaths, UNICEF, WHO, the UNFPA, and the AMDD (Averting Maternal Death and Disability) initiative through Columbia University identified a set of nine 'signal functions' and common facility indicators (WHO et al., 2009). Using this framework, facilities are classified as either Basic EmOC facilities, or facilities offering 1) parenteral antibiotics, 2) uterotonic drugs such as parenteral oxytocin, 3) parenteral anticonvulsants for pre-eclampsia and eclampsia, 4) manual removal of placenta, 5) removal of retained products, 6) assisted vaginal delivery, and 7) basic neonatal resuscitation. Facilities offering these services plus 8) surgery such as caesarean section and 9) blood transfusion, are classified as comprehensive EmOC facilities (Paxton et al., 2005; WHO et al., 2009).

To assess the impact of EmOC interventions on preventing maternal deaths in developing countries, Paxton and colleagues performed a systematic literature review including studies with evidence from over 80 countries. Reviewing studies with a variety of experimental designs such as quasi-experimental, observational and ecological designs, they found strong consensus that incorporating EmOC facility coverage into national programme strategies is a key component in reducing maternal mortality among developing countries (Paxton et al., 2005). Specifically, among a sample of 12 countries with varying degrees of met need for emergency obstetric services, a preliminary correlation analysis showed that estimated maternal mortality ratio (MMR), or maternal deaths per 100,000 live births, was inversely associated with a higher degree of met need for EmOC ($R^2 = 0.64$). These findings indicate that countries having higher proportions of women who receive the emergency care they required (and therefore wider EmOC facility coverage), tended to also have lower estimated maternal mortality ratios (Paxton et al., 2005).

In 2006, Paxton and colleagues followed this systematic review up by examining standardized needs assessment created through the AMDD program at Columbia University throughout 24 countries, with aims of reporting global trends of EmOC facility coverage (Paxton et al., 2006). Out of this analysis, they report three key themes which emerged: 1) the minimum number of comprehensive EmOC facilities required in relation to population size were typically available among even the least-developed countries; 2) the number of basic EmOC facilities, however, were typically not sufficient, even among countries with only moderate levels of maternal mortality; and, 3) the majority of facilities surveyed were not able to satisfy the full spectrum of recommended interventions comprising key signal functions. As a result of this analysis, Paxton and colleagues therefore recommended that existing facilities such as hospitals and maternity care wards be 'upgraded' to qualify as meeting basic EmOC facility standards (Paxton et al., 2006).

2.1.4 Barriers to utilisation of health services

Care packages focusing only on increasing the absolute number of MNH care services may miss a crucial component of why emergency complications can turn into fatalities. Integration of successful intervention packages requires a detailed understanding of the socioeconomic and health systems barriers surrounding the decision to seek and obtain care on both the supply and demand side. Here, the seminal three-delay model is discussed as proposed by Thaddeus and Maine, followed by a discussion of common economic supply and demand-side barriers influencing affordability, acceptability, and quality of care provided.

2.1.4.1 Three-delay framework

The vast majority of obstetric complications can be prevented through routine health services, such as antenatal care or skilled birth attendance, or treated through timely identification and prevention (Bailey et al., 2006). Despite this, the duration between a woman's decision to seek care to that of actually obtaining the care is fraught with delays, thereby preventing life-saving treatment and contributing to morbidity and mortality. Thaddeus and Maine articulated this process when they proposed the three-delay model framework, suggesting phases of delays exist in 1) the decision to seek care, 2) the accessibility of a health facility, and 3) the provision of adequate care (Thaddeus and Maine, 1994). Within the first phase, the decision to seek care is shaped by broad socioeconomic and cultural compositional factors, including demand-side factors and decision-making behaviours outside of the woman's control, such as those by her husband or mother-in-law. For example, Byrne and colleagues found among a synthesis of studies that delayed care-seeking behaviours in the mountainous regions of Nepal was determined by costs of care-seeking, traditionally held beliefs, lack of knowledge, dissatisfaction with quality of care, and low autonomy of a woman in obtaining her care (Byrne et al., 2013). Importantly, these delays in care-seeking behaviour only served to further exacerbate later delays.

Once the decision to seek care has been made, challenges in accessing care may be encountered through the physical landscape such as mountainous terrain, transportation, or long distances to the nearest health facility. Gething and colleagues explored the accessibility delay within an explicitly geographical context in Ghana, finding that over a third of women lived beyond a 2-hour journey to the nearest facility offering basic or partial emergency obstetric care (EmOC) (Gething et al., 2012). These findings were further exaggerated amongst the most remote regions, with upwards of 80% of women living within "accessible" distance, or less than a 2-hour journey, to a comprehensive EmOC facility.

Gabrysch and Campell further explored how physical accessibility affects service utilisation, specifically in the context of the three delay model, as shown in Figure 2.7 (Gabrysch and Campbell, 2009a). In their literature review, they found the vast majority of studies explore region and place of residence, while fewer studies have explored distance or travel time and transport to facilities, despite its impact on both the decision to obtain care and the accessibility of that care. The incorporation of geospatial data sources with explicitly geographical approaches are arguably crucial in supporting systemic maternal care planning, yet remain underutilised (Ebener et al., 2015; Gabrysch and Campbell, 2009a; Gething et al., 2012). With the growing availability of georeferenced data, however, opportunities are arising to link these data sources with maternal health outcomes, and represent a promising new avenue of research (Ebener et al., 2015; Gabrysch and Campbell, 2009a).

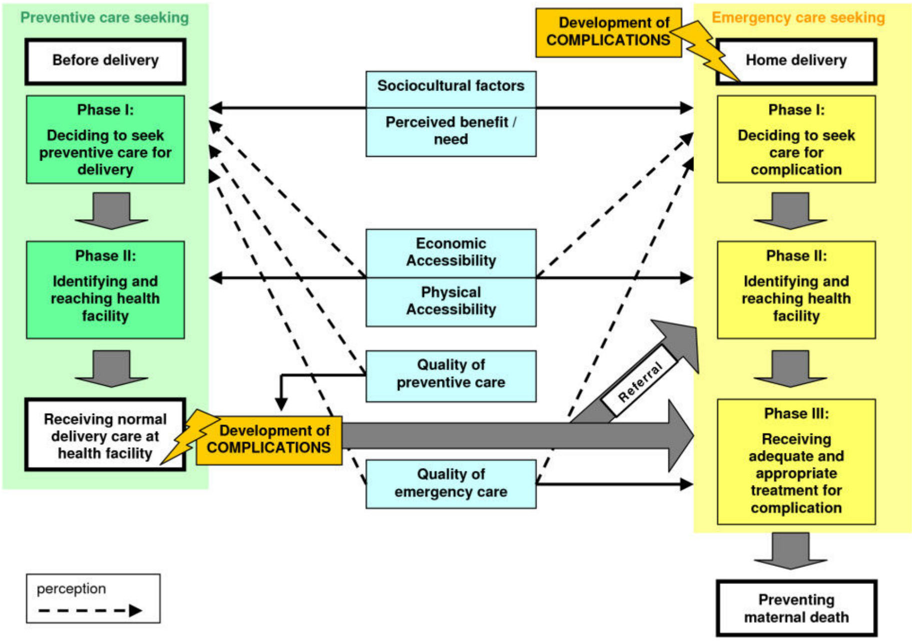


Figure 2.8 Phases of delay and factors affecting utilisation of maternal health services, as published by Gabrysch and Campbell, 2009

The final phase of delay, provision of adequate care, is predominantly driven by quality of care provided. Thaddeus and Maine argue this is explained by satisfaction or dissatisfaction with the service received and outcome, noting that these mechanisms are driven by perceived quality of care, rather than medical quality, potentially conflicting with patient perceptions (Thaddeus and Maine, 1994). This conflict is echoed by Gabrysch and Campbell, who note that studies found medical culture often clashed with traditional beliefs, resulting in a lack of respect or cultural competence which impacted perceived quality of care (Gabrysch and Campbell, 2009a). Despite its importance in driving the decision to seek care and the timeliness in ultimately receiving that care, few quantitative studies have examined quality of care, and even fewer within a geographical construct. Gabrysch and Campbell argue this could be due to a number of restraints between linking individual level data with facility-based data. Yet with the growing of availability of georeferenced facilities, household and individual surveys, and spatially explicit Health Management Information systems (HMIS), future research may be able to examine quality of care and its interaction with physical accessibility and facility choice.

2.1.4.2 Supply and demand side barriers

A plethora of economic barriers in accessing care on both the supply and demand side influence an individual's decision to seek, access, and obtain care. Ensor and Cooper outlined this clearly in their review of demand-side barriers in low- and middle-income countries, and present suggestions for how to overcome these barriers (Ensor and Cooper, 2004). They begin by defining 'demand' side barriers as those "factors that influence demand and operate at the individual, household or community level". These may include factors such as lack of knowledge of obstetric complications or available services, high financial costs in accessing care, lack of empowerment in making decisions about seeking care, religious objections, etc.

Alternatively, 'supply' side barriers are those "that influence the slope and position of the supply curve", and may manifest as lack of adequate medicine, equipment or personnel, a lack of nearby health facilities, difficulty in obtaining a referral to a given hospital, or a lack of respect or cultural competence among health staff. Ensor and Cooper go on to further categorize these demand side barriers, suggesting barriers can be broadly grouped into: 1) information on health care choices/providers, 2) education, 3) indirect consumer costs such as distance and opportunity costs, 4) household preferences, 5) community and cultural preferences, attitudes and norms, and 6) price and availability of substitute services. By grouping barriers into these categories, they argue interventions may be targeted to overcome these obstacles, including improved education, provision of transportation to health services, financial restitution for lost wages in accessing care, and targeted subsidies for the most vulnerable members of households (Ensor and Cooper, 2004).

Jacobs et al. further explore both supply and demand side barriers in their literature review of barriers in accessing care, and incorporate dimensionality of barriers as they relate to geographic accessibility, availability, affordability and acceptability (Jacobs et al., 2012). They build upon Ensor and Cooper's work on demand side barriers, and further outline several supply side barriers within these dimensions: service locations affecting geographic accessibility; waiting times, staff qualifications and stock of drugs or other equipment affecting availability; costs and prices of services affecting affordability; and staff interpersonal skills and cultural attitudes, including trust, affecting acceptability.

They further note potential interventions targeting these crucial supply side barriers, including provision of essential health services, regulatory approaches, integrated outreach services, provision of maternity waiting homes, emergency transport and adequate facility staffing, and increased education on culturally sensitive health care delivery (Ensor and Cooper, 2004; Jacobs et al., 2012). They note that interventions exist addressing all four dimensions of access barriers but do not address both supply and demand side barriers, while other less comprehensive interventions may touch upon only a few dimensions influencing both supply and demand side barriers. As a result, no one intervention can be considered a 'magic bullet' approach, and often successful approaches to reducing these barriers rely on a combination of interventions (Jacobs et al., 2012; McNamee et al., 2009).

2.1.4.3 Quality of care barriers

The existence, accessibility and provision of care does not, however, guarantee that women will use these services, nor does it guarantee improved health outcomes for the woman or child. Hulton and colleagues argue that only provision of high quality, acceptable care can necessitate both timely use and improved maternal and newborn mortality metrics (Hulton et al., 2000). Indeed, among the most marginalised groups within the least developed countries, numerous studies have reported the correlation between low quality of care measures and high rates of maternal and newborn mortality (van den Broek and Graham, 2009). While the specific mechanisms which drive the relationship between health seeking behaviour and quality of care are not well understood, studies have noted that a woman's perception of quality of care can often predict facility choice more than proximity (Hulton et al., 2000). Hulton and colleagues argue these perceptions are shaped by both the experience of care and the provision of care. They go on to report case studies where too often women are provided with inadequate information about what services are being provided to them, are not treated with dignity or respect, such as a lack of privacy during examination, or are sometimes ignored altogether and left to labour in crowded waiting rooms without acknowledgement (Hulton et al., 2007).

Yet despite its importance in predicting health seeking behaviour and in influencing utilisation of maternity services, quality of care within maternal health has been historically neglected, with no universal definition of "quality of care" nor systematic frameworks by which to assess quality of care in maternity services (Hulton et al., 2000; van den Broek and Graham, 2009). To address this need, Hulton and colleagues proposed a framework by which to assess quality of care, incorporating key elements influencing the experience of care and the provision of care (Figure 2.8) (Hulton et al., 2000). They argue that experience of care is influenced by: a woman's perception of the human and physical resources available to her at a health facility; her awareness and understanding of the situation; the perceived respect, dignity and equity afforded to her by staff; and the emotional support received during care.

On the other side of 'quality of care' is a facility's provision of care, which can be reflected by: the objective quality of human and physical resources available; the quality of the referral systems and health management systems in country; the use of adequate and appropriate technology in maternity care; and lastly, the use of and adherence to internationally recognised good practice procedures (Hulton et al., 2007). With the proposal and application of this framework, 'quality of care' can be objectively assessed and monitored, and indeed represents a neglected agenda which has historically failed to be incorporated into key global strategies and intervention efforts (van den Broek and Graham, 2009).

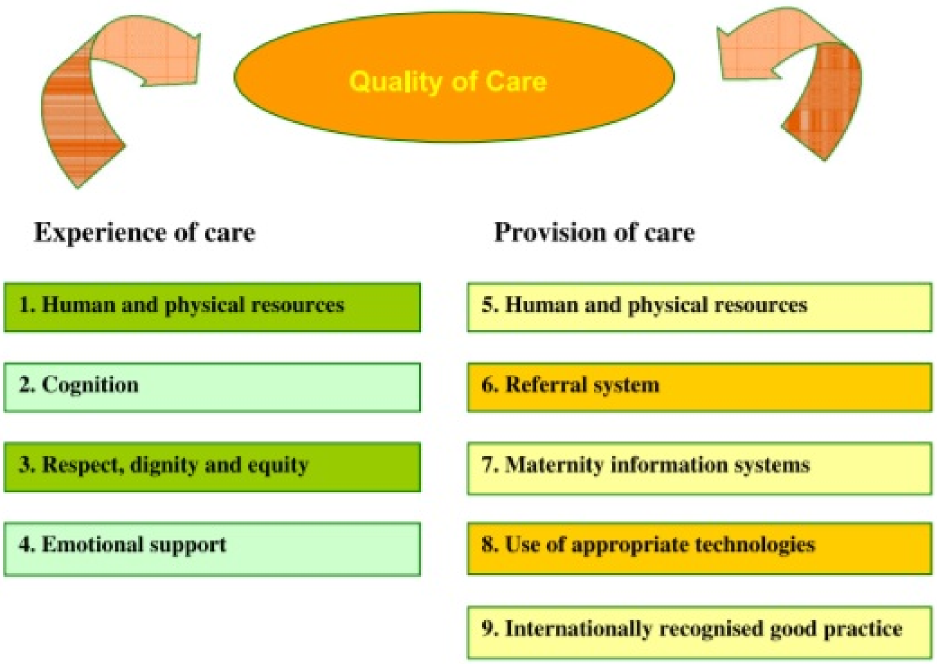


Figure 2.9 Framework for assessing quality of care in maternity services, as published by Hulton et al., 2007

2.1.5 Monitoring maternal and newborn health outcomes in the SDG era

Establishing a standardized and rigorous framework by which to monitor and evaluate progress in maternal and newborn health will be key to achieving meaningful reductions in maternal and newborn deaths, as well as ensuring greater well-being for all. Since the development of the MDGs in 2000, international agencies around the world have agreed on a short list of key indicators such as maternal mortality ratio, antenatal care coverage, births attended by skilled health personnel, contraceptive prevalence, etc., to be used in monitoring the progress of global reproductive health (WHO, 2006). The WHO outlined a subset of these indicators, together with indicators relating to newborn and child health, to be used as key targets in MDGs 4 and 5, which have continued into the SDG platform under target 3 (Table 2.1). Despite these guidelines, debate surrounding how to measure these key indicators persists, and definitions used among indicators, such as what constitutes 'skilled health personnel', vary widely between countries (Adegoke et al., 2011; Victora et al., 2016).

Table 2.1 Selected MDG and SDG targets and indicators pertaining to maternal and newborn health

Millennium Development Goal Targets and Indicators (2000 – 2015)		
Goal 4: Reduce child mortality		
	Target	*Indicator*
Target 4A	Reduce by two-thirds, between 1990 and 2015, the under-five mortality rate	4.1: Under-five mortality rate
		4.2: Infant mortality rate
		4.3: Proportion of 1 year-old children immunized against measles
Goal 5: Improve maternal health by 2015		
Target 5A	Reduce by three-quarters, between 1990 and 2015, the maternal mortality ratio	5.1: Maternal mortality ratio (MMR)
		5.2: Proportion of births attended by skilled health personnel
Target 5B	Achieve by 2015 universal access to reproductive health	5.3: Contraceptive prevalence rate
		5.4: Adolescent birth rate
		5.5: Antenatal care coverage (at least one visit and at least four visits)
		5.6: Unmet need for family planning
Sustainable Development Goal Targets and Indicators (2015 – 2030)		
Goal 3: Ensure healthy lives and promote well-being for all at all ages		
	Target	*Indicator*
Target 3.1	By 2030, reduce the global maternal mortality ratio to less than 70 per 1000,000 live births	3.1.1: Maternal mortality ratio
		3.1.2: Proportion of births attended by skilled health personnel
Target 3.2	By 2030, end preventable deaths of newborns and children under 5 years of age, with all countries aiming to reduce neonatal mortality to at least as low as 12 per 1,000 live births and under-5 mortality to at least as low as 25 per 1,000 live births	3.2.1: Under-five mortality rate
		3.2.2: Neonatal mortality rate
Target 3.8	Achieve universal health coverage, including financial risk protection, access to quality essential health-care services and access to safe, effective, quality	3.8.1: Coverage of essential health services (defined as the average coverage of essential services based on tracer interventions that include reproductive, maternal, newborn and child health, infectious

	and affordable essential medicines and vaccines for all	diseases, non-communicable diseases and service capacity and access, among the general and the most disadvantaged population)
		3.8.2: Number of people covered by health insurance or a public health system per 1,000 population
Target 3.c	Substantially increase health financing and the recruitment, development, training and retention of the health workforce in developing countries, especially in least developed countries and small island developing States	3.c.1: Health worker density and distribution

Evidence shows that the majority of maternal deaths occur around the time of labour, delivery, and the immediate postpartum period (Ronsmans and Graham, 2006). Therefore, the reduction and prevention of adverse maternal and newborn health outcomes will require a focused understanding of individual risk before, during and after delivery, in addition to a facility-level understanding of accessibility to skilled workforce, emergency services, and the quality of services provided (Kerber et al., 2007; Requejo and Bhutta, 2015). Improving fundamentally multidimensional maternal and newborn health outcomes, however, necessitates targeted efforts and quantifiable indicators of progress. Towards this, monitoring and evaluation frameworks have been applied to identify structural indicators, input process and resulting outcomes which can be used to monitor progress effectively and efficiently (WHO, 2010a, 2016a).

2.1.6 Inequalities in maternal and newborn health

The MDGs prioritised a reduction in national level development indicators such as overall poverty or literacy, with a focus on ensuring rates between countries were more equitably distributed. Little focus, however, was paid to within-country inequalities, and indeed while national progress improved, pockets of localized, hidden disparities containing the most vulnerable populations persisted (Bhutta ZA and Reddy K, 2012). The SDGs agenda aims to address this oversight with Goal 10 specifically calling for reduction in inequalities both between and within countries, stressing “no one left behind” (Hosseinpoor et al., 2015). Disaggregated data comparable across countries will be key to achieving these targets and monitoring the reduction of inequalities both nationally and sub-nationally, and indeed other SDG targets call on countries to increase high-quality, readily accessible data, disaggregated by geographic location and socio-economic indicators such as race, age, and income. The WHO’s Health Equity Monitor has led the way on best practices in compiling databases which consist of disaggregated, comparable data spanning nearly 100 low- and middle-income countries, and reporting how these inequalities should be monitored and evaluated over time and space (Hosseinpoor et al., 2015; WHO, 2015a).

In this seminal report, the WHO's Health Equity Monitor focused on inequalities within the field of reproductive, maternal, newborn and child health (RMNCH), noting that inequalities persisted both between and within countries in terms of maternal health outcomes and intervention coverage (WHO, 2015a). Specifically, they noted the largest disparities were found "between the richest and poorest, the most and least educated, and urban and rural areas", among skilled birth attendance (Figure 2.9) and 4+ antenatal care visits, followed by use of modern contraception (Figure 2.10) and immunization coverage (Figure 2.11). Just as inequalities evolve over space, however, they have also changed and improved over time, with national figures increasing over the previous decade, and some countries noting more rapid rates of improvement among vulnerable sub-populations within country.

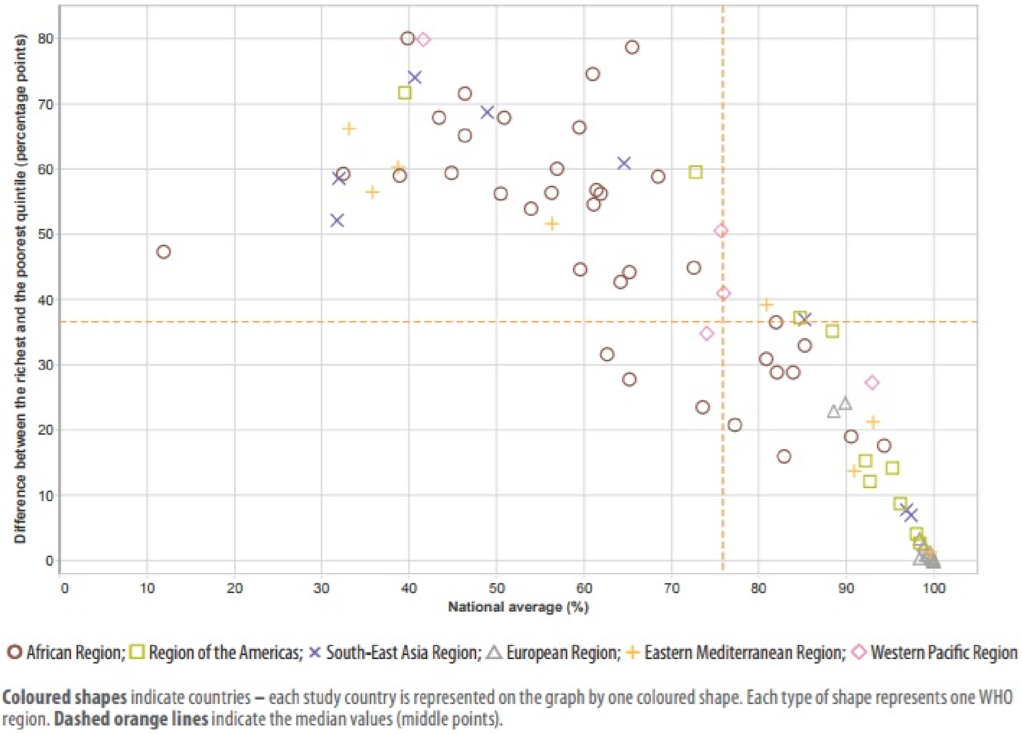
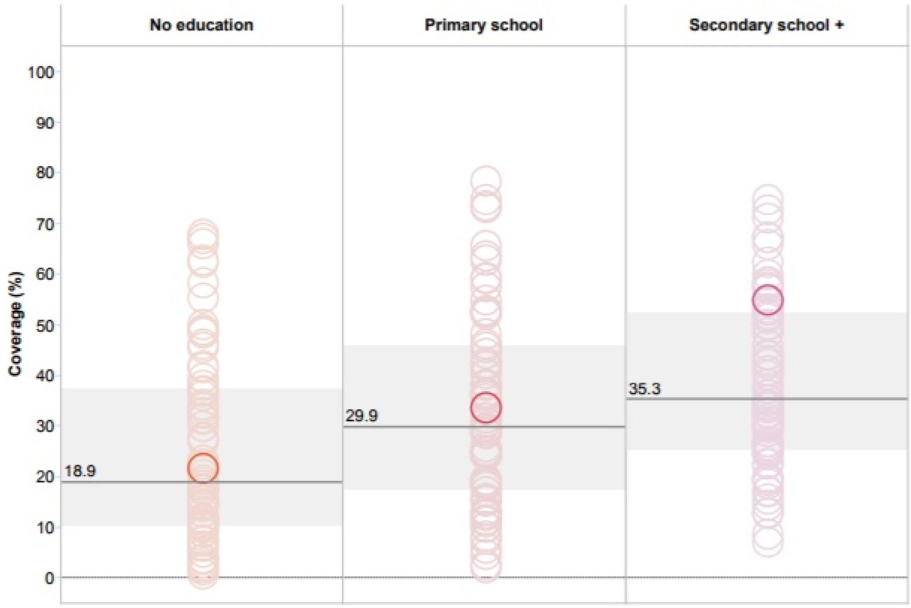
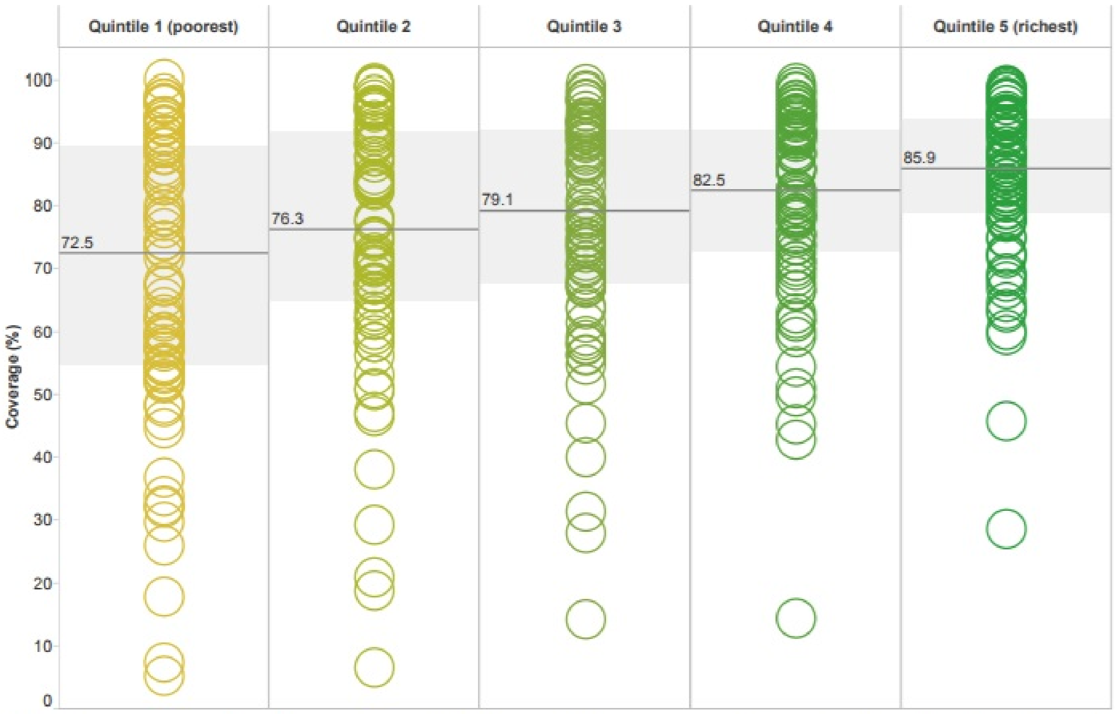


Figure 2.10 Skilled birth attendance in 83 low- and middle-income countries, as published by WHO 2015a



Circles indicate countries – each study country is represented on the graph by three circles. **Horizontal lines** indicate the median value (middle point) for each subgroup. **Light grey bands** indicate the interquartile range (middle 50% of study country estimates). **Highlighted country**: Ethiopia.

Figure 2.11 Modern contraceptive prevalence among 71 low- and middle-income countries, as published by WHO 2015a



Circles indicate countries – each study country is represented on the graph by five circles. Horizontal lines indicate the median value (middle point) for each subgroup. **Light grey bands** indicate the interquartile range (middle 50% of study country estimates).

Figure 2.12 DTP3 immunization coverage among 78 low- and middle-income countries, as published by WHO 2015a

For example, in half of the countries included within the WHO report, immunization coverage for polio and DTP3 were 'pro-poor', with children in the poorest quintiles having margins of nearly 10 points greater than children in the wealthiest quintiles, as shown in Figure 2.12 (WHO, 2015a).

However, some gains in intervention coverage over time varied even by socioeconomic status, such as unmet demand for family planning. Specifically, this indicator saw improvements over time by education (with those in the least educated group having a higher rate of increase in met demand, as compared to those with secondary education or higher), but with slower rates of increase among those in rural areas. These findings suggest the complicated future of monitoring disaggregated data within the post-2015 SDG era. This implies that in order to track the progress of maternal and newborn health within countries (and importantly, how this progress manifests within all populations), a multidisciplinary approach is needed, tracking outcomes disaggregated by geography, time, and socioeconomic status.

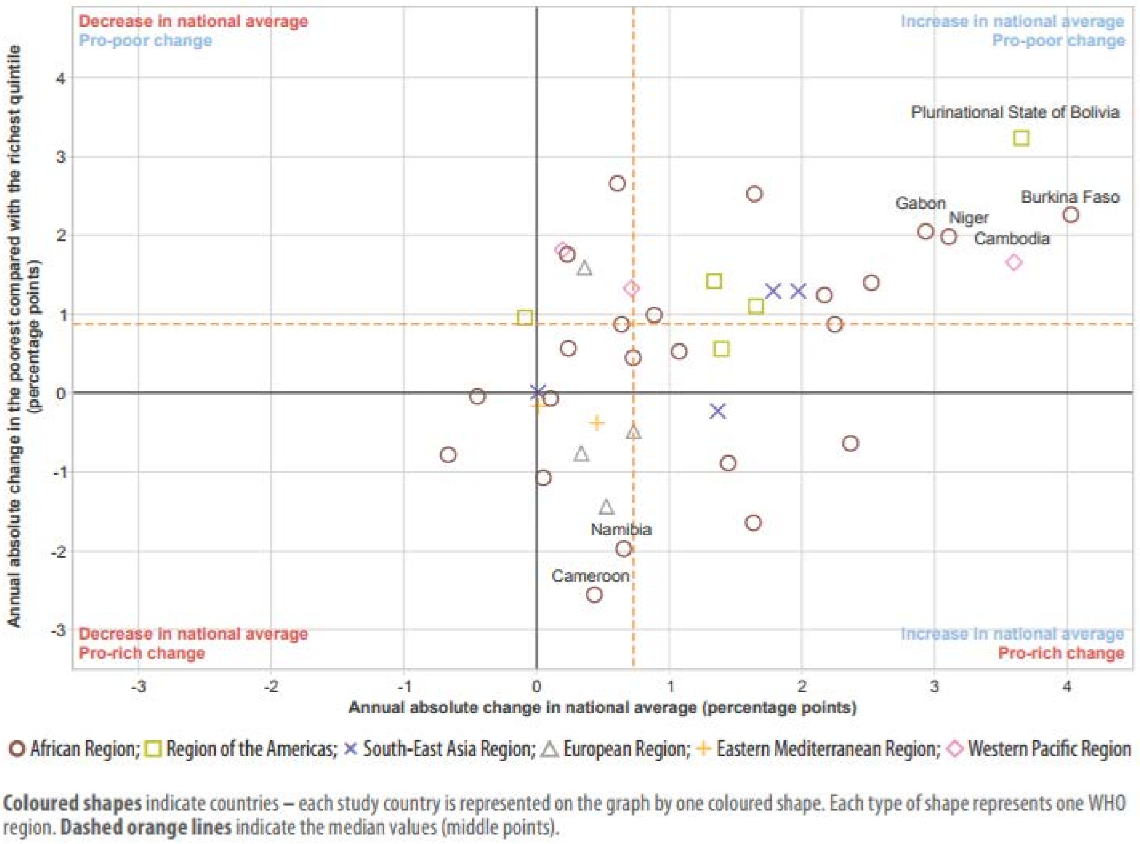


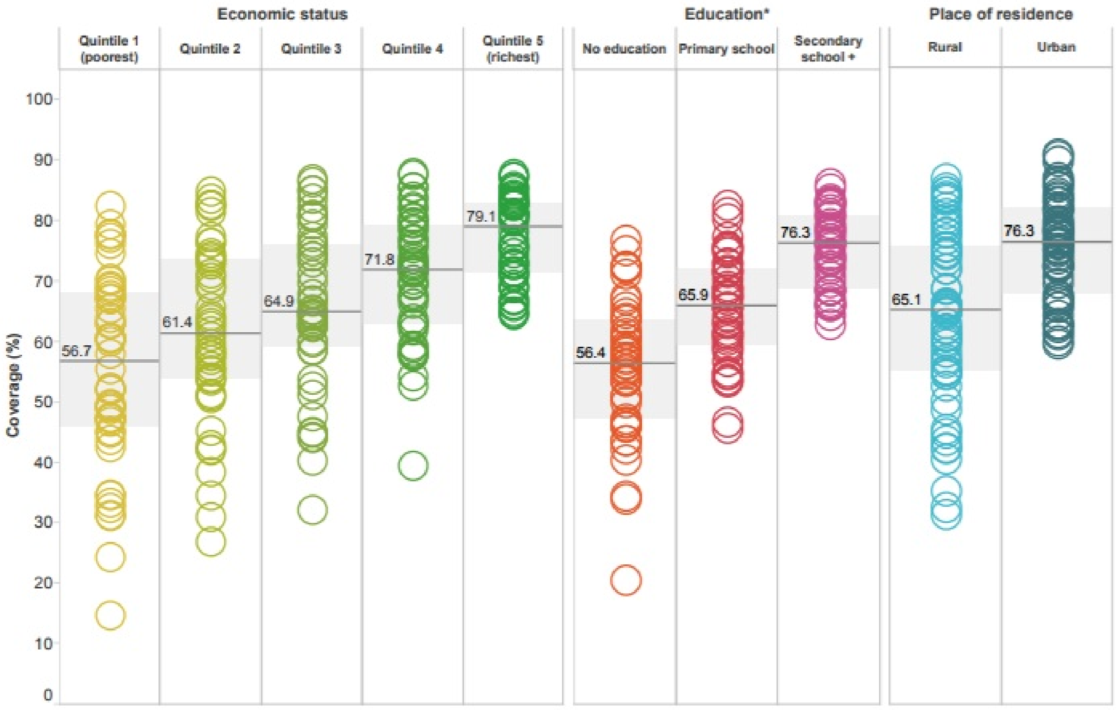
Figure 2.13 Change over time (absolute and absolute excess change) in DTP3 immunization coverage among 41 low- and middle-income countries, as published by WHO 2015a

2.1.6.1 Measuring inequalities

Monitoring and evaluating progress towards achieving SDGs will rely not only on individual and facility level indicators, but also coverage of one or many interventions. Towards this, several approaches exist quantifying coverage among a set of interventions, including co-coverage, composite coverage, and effective coverage indices. A co-coverage score can be calculated to reflect what proportion of the population is receiving a set of interventions, typically among a set of essential or lifesaving interventions (Victora et al., 2005). This index can be helpful in identifying to what extent women and children are receiving a set of complimentary interventions, but can also prove analytically intensive as it requires reanalysis of input survey data (Barros and Victora, 2013).

Alternatively, the composite coverage index score represents a weighted score among a set of essential interventions, providing information on the overall coverage of a set of intervention services, with emphasis (or weight) of each constituent service varying across the continuum of care as determined by the researcher (Boerma et al., 2008). This score can prove more computationally efficient, particularly across multi-country analyses or time-trend assessments, particularly where a single, group-level estimate is desired (Barros and Victora, 2013). Lastly, an effective coverage score can be calculated, representing health systems' performance score by combining information quality of care, need and use of services of interest. This approach reflects not only the proportion of the population or individuals using the service, but also adjusts for service use by the quality of care of the service provided (Nguhiu et al., 2017).

This approach can be effective in prioritizing country-specific priorities, as well as estimating inequalities among particular sub-groups. The WHO exemplified this approach when calculating a composite coverage index highlighting 8 key RMNCH interventions, including met demand for family planning, ANC coverage, SBA, BCG/DTP3/measles immunization coverage, health seeking behaviour among children with pneumonia symptoms, and oral rehydration therapy for children with diarrhoeal diseases (WHO, 2015a). By combining these interventions into one easily interpretable score, inequalities over space, time and socioeconomic characteristics can be reported, as exemplified in Figure 2.13 where the composite coverage indicator score is presented for several socioeconomic characteristics.



* Education refers to the highest level of schooling attained by the woman or, in the case of newborn and child health interventions, the child's mother. **Circles** indicate countries – each study country is represented on each graph by one circle per subgroup. **Horizontal lines** indicate the median value (middle point) for each subgroup. **Light grey bands** indicate the interquartile range (middle 50% of study country estimates).

Figure 2.14 Composite coverage index for 8 selected RMNCH interventions in selected low- and middle-income countries, as reported by WHO 2015a

2.2 Spatial demographic data for health in Sub-Saharan Africa

With recent advancements of more computationally efficient resources and user-friendly applications, the past decade has seen an exponential rise in applications of geographical information systems (GIS) towards addressing public health research questions (Banerjee, 2016). Adoption and uptake of GIS techniques within public health has generally been slower within Africa, however, due to a number of obstacles such as infrastructure and cost constraints, lack of donor investment involving capacity strengthening and local engagement, and lack of sustainable research funding moving past the donor-led phase of research projects (Tanser and le Sueur, 2002). Despite this, GIS tools offer great potential in addressing some of the most significant public health threats facing the African continent, particularly in the context of MNH (Ebener et al., 2015; Molla et al., 2019, 2017).

Over the coming decades, data visualization and disaggregation through disease mapping and spatial analysis can play an increasingly significant role in ensuring that preventable maternal and newborn deaths are avoided and disease burden is lessened amongst the most vulnerable populations (Molla et al., 2017; Tanser and le Sueur, 2002). Despite this, monitoring MNH trends over time and space remains limited due to unreliable spatial data, lack of expertise and capacity within countries, and inconsistent data production resulting in conflicting results (Molla et al., 2019). Avoiding preventable deaths therefore necessitates that these challenges are adequately addressed and recommendations made in ensuring high quality spatial data that can be collected even within resource-poor settings.

In this section, I address current trends and emerging innovations in freely available spatial demographic data production that can be used in GIS applications throughout Africa. Firstly, I outline the utilisation of GIS techniques and availability of spatial demographic data in Africa, followed by the evolution of methods and current approaches used to estimate these data, where other reliable sources might be lacking. I then present case studies highlighting applications in producing freely available spatial demographic data, including subnational age and gender composition, high-resolution live births and pregnancies, and quantifying human mobility derived from mobile phone data. Lastly, I discuss gaps in knowledge in improving the production of spatial demographic data, and applications to low-resource settings and policy-making.

2.2.1 GIS utilisation and the availability of spatial demographic data

2.2.1.1 GIS utilisation within Africa

With an increasing number of health researchers adopting GIS techniques, the potential to explore spatial variation in disease and its relationship to the environment, population, and health systems is growing. The application of these methods can be limited, however, by infrastructure and cost constraints, as well as specialist knowledge capacity. While GIS can help to fill these gaps, the technology must be aimed at health problems and priorities relevant to the region. Towards this, (Tanser and le Sueur, 2002) performed a systematic review of the health literature within African settings at the turn of the millennium, examining GIS research amongst top public health threats within Africa, such as HIV/AIDS, malaria, and tuberculosis. Overall, they found that GIS applications have been widely applied within Africa to diseases with strong environmental components, such as malaria elimination settings, but fewer studies have utilized GIS to study non-vector borne diseases such as tuberculosis and HIV/AIDS. Despite the ability to address research questions central to African health issues, they note that the use of GIS techniques remained underutilized, and suggested a need for greater capacity strengthening efforts to train GIS experts within-countries (Tanser and le Sueur, 2002).

Yet with global trends favouring more powerful computational techniques and hardware, greater availability of user-friendly software, and increasing reliability of demographic data collection and vital health registrations, the use of GIS continues to hold promise for addressing health research priorities and policy planning within Africa (Tanser and le Sueur, 2002). More recently, Ebener and colleagues performed a rapid literature review over a decade later to examine utilisation of GIS techniques within the field of maternal health (Ebener et al., 2015). Overall, they note that despite the increasing interest and promise in the use of GIS techniques to address health problems, methods remained largely underutilized within the field of maternal and newborn health in low- and middle-income countries. Specifically, they report three primary emerging areas of research within the field: 1) thematic mapping (i.e., choropleth maps conveying information on a topic or theme), 2) spatial analysis (i.e., creation of new information using spatial data), and 3) spatial modelling (i.e., statistical or mathematical models simulating a spatial process or phenomena). Despite the emergence of these broad research areas, they recommend better communication and coordination amongst institutions to build GIS capacity and expertise, including amongst in-country health sectors and non-academic institutions (Ebener et al., 2015).

2.2.1.2 Availability of spatial demographic data

However, to facilitate greater application and uptake of GIS methods in addressing health research questions specific to Africa, reliable, high-resolution, and contemporary spatial data is necessary which is also freely available. Over recent decades, the use of spatially explicit demographic data, particularly quantifying human population distributions, has seen broad applications across spatial epidemiology, urban planning, accessibility modelling, disaster management, resource allocation, and more (Tatem et al., 2012, 2007).

Towards this, Tatem and colleagues outline several freely available sources of spatially explicit data (Table 2.2) to inform demographics such as population counts, age and gender composition, urbanization, etc., including census data, census microdata, and survey data. Figure 2.15 displays the availability of these datasets by country, as published by Tatem et al., 2012. This figure represents (a) the number of census microdata records freely available through the International Public Use Microdata Series repository (https://international.ipums.org/international/), (b) the combined number of DHS, AIDS Indicator Surveys (AIS), and Malaria Indicator Surveys (MIS) surveys conducted for each country, and (c) the combined number of DHS, AIS, and MIS surveys available with GPS coordinates available (Tatem et al., 2012). While these sources may not represent a comprehensive list of available datasets, and crucially do not contain information on availability of HMIS data, they nevertheless represent major venues of freely available geospatial demographic data accessible across low and middle-income countries.

Table 2.2 Sources of spatially explicit demographic data, as outlined by Tatem et al., 2012

Data (standard survey name)/source	**Time intervals**	**Typical spatial coverage**	**Typical strata**	**Relevant variables**
Census				
National Statistical Offices	Typically 10 years	Census enumerator area or courser level	Urban/rural, race or ethnic groups (often)	Sex, age, education, migration status, household and dwelling characteristics
Census Microdata				
https://international.ipums.org/international/	Typically 10 years	Admin 1-3	Urban/rural	Household and dwelling characteristics, sex, age, education, migration status, children ever born, children surviving
DHS (Demographic and Health Survey)				
Household, women 15–49, men 15–59, children born in the last five years				
http://www.measuredhs.com/	Varies by country, typically every 5 years	National, Admin 1/region, GPS coordinates of cluster locations for	Urban/rural	Household and dwelling characteristics, sex, age, education, maternal and child health, fertility and full birth history, family planning, domestic

Data (standard survey name)/source	Time intervals	Typical spatial coverage	Typical strata	Relevant variables
		most recent surveys (last 15 years)		violence, biomarkers, nutrition
MICS (Multi-indicator cluster survey)				
http://www.unicef.org/statistics/index_24302.html	UNICEF (Round 2, 1999–2001; round 3 2005–2007; round 4 is in the field 2009–present)	National, Admin 1	Urban/rural	Household and dwelling characteristics, sex, age, education, status, maternal and child health, child labour, domestic violence, summary birth history, anthropometry
LSMS (Living Standard Measure Survey)				
(Integrated Household Budget Survey and many others that are locally adapted)				
http://iresearch.worldbank.org/lsms/lsmssurveyFinder.htm	Irregular	National, Admin 1, some GPS coordinates	Urban/rural	Household and dwelling characteristics, sex, age, education, migration status, consumption, expenditures, income, nutrition, anthropometry, summary birth history

Data (standard survey name)/source	Time intervals	Typical spatial coverage	Typical strata	Relevant variables
MIS (Malaria Indicator Survey)				
http://www.measuredhs.com/				
http://www.malariasurveys.org/	Varies by country, typically every 3 years	National, Admin 1/region, GPS coordinates of cluster locations for some surveys (last five years)	Urban/rural	Household and dwelling characteristics, sex, age, education, biomarkers
AIS (AIDS Indicator Survey)				
http://www.measuredhs.com/	Varies by country, typically every 3 years	National, Admin 1/region, GPS coordinates of cluster locations for some surveys (last eight years)	Urban/rural	Household and dwelling characteristics, sex, age, education, biomarkers

Census data represent some of the most detailed information regarding spatial demographic data within a country (Hay et al., 2005), typically carried out around once every 10 years (Tatem et al., 2012), and in more recent decades often include harmonization into digital census databases (Balk et al., 2006). However, while high-income countries have extensive resources available to conduct census surveys, low-income countries can suffer from constraints in resources, lack of knowledgeable experts, and competing development priorities, with the most recent mapping and census efforts for some countries occurring thirty to forty years ago (Tanser and le Sueur, 2002; Tatem et al., 2007). In addition, these data can be aggregated to bespoke and irregular administrative units based on enumeration areas (Balk et al., 2006), and are often proprietary and difficult to obtain. To supplement these challenges as well as fill in temporal gaps, census microdata are comprised of large, representative subsamples of households surveyed during a census generally stored in data repositories like the International Public Use Microdata Series (https://international.ipums.org/international/), making data easier to obtain than full censuses. These data may be available at smaller spatial units than typical surveys, with similar levels of spatial demographic data such as age, gender, population, etc. (Tatem et al., 2012).

Survey data collected through international survey programmes such as the Demographic and Health Surveys (DHS), Multiple Indicator Clustery Survey (MICS), and AIDS Indicator Survey (AIDS) are collected on regular intervals and standardized across countries to allow for comparison across borders. These surveys represent some of the primary sources of information on demographic data such as fertility, health, family planning, maternal and child health, provision of health services, and more (Burgert and Prosnitz, 2014), and further allow links between individual household survey data and health facility data. Not only are these data rich in demographic and health information on local populations, but they are becoming increasingly spatially detailed, as represented by geo-referencing of clusters among DHS surveys (Burgert et al., 2013). Further, these data are freely available to researchers across the world (Figure 2.15), and therefore represent a promising avenue for obtaining spatial demographic data, particularly amongst developing countries.

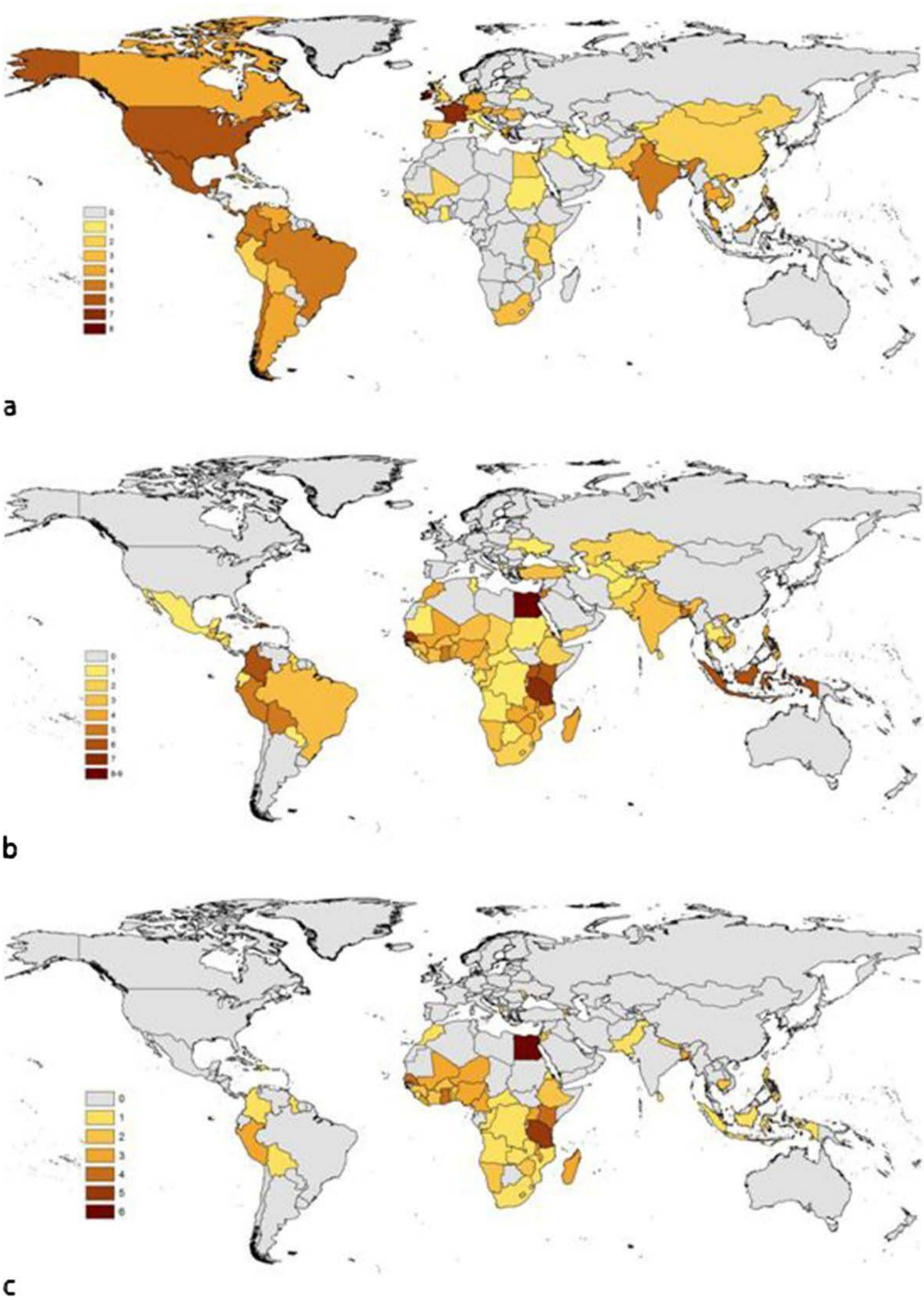


Figure 2.15. Availability of demographic datasets informing subnational population attributes, among a) census microdata, b) national household survey programmes, and c) national household survey programmes with corresponding GPS information. Adapted from (Tatem et al., 2012)

Lastly, many countries across Africa rely on country-wide health management information systems (HMIS) for routine health data and disease surveillance (Gething et al., 2006). These systems, when regularly updated and uniformly applied, can result in reliable and timely information that can be used to robustly monitor and evaluate a variety of public health conditions. This is especially pertinent in resource-limited settings, where interventions and funds must be strategically and efficiently allocated (Health Metrics Network, 2008). Over recent years, HMIS systems are increasingly providing geo-located data at the health facility-level, where data is collected and then compiled at the regional and national level. In a highly functioning HMIS setting, this results in large datasets which can be analysed at both high spatial resolutions and across fine temporal scales, such as monthly estimates. Despite this, the reality of HMIS settings within Africa is less than ideal, with many countries facing competing priorities, resulting in poor data coverage and incomplete routine surveillance efforts (Gething et al., 2006; Health Metrics Network, 2008). Regardless, HMIS remain a robust and underutilised source of spatial health data, holding promise for further strengthening over the coming years.

Yet in the absence of contemporary sources of spatial data, in addition to decentralized, uncoordinated efforts that can often lead to conflicting, unreliable data sources, the production of spatial demographic data in resource-poor settings often relies upon augmentation with ancillary, satellite-derived data sources (Molla et al., 2017; Tatem et al., 2007). These data sources may include proximity to roads, elevation and land cover, human settlement locations, distance to nearest urban centre, night-time lights, and more (Dobson et al., 2000; Tatem et al., 2012), and are often employed in geo-statistical models to predict distributions of human populations (Balk et al., 2006), including age and gender composition (Pezzulo et al., 2017), births and pregnancies (Tatem et al., 2014), and development indicators such as literacy and childhood stunting (Bosco et al., 2017).

Mapping efforts utilizing these data sources have grown over the past few decades, evolving from simple areal weight redistribution methods (Tatem et al., 2007) to more sophisticated machine-learning approaches requiring computationally intensive time and resources (Stevens et al., 2015; Wardrop et al., 2018). In the following sections, we discuss the evolution of efforts to map demographic data, as well as current approaches in quantifying human population distributions at a high spatial resolution.

2.2.2 The evolution of mapping demographic data and current approaches

2.2.2.1 The evolution of mapping demographic data

Global populations are rapidly changing, with more than 50% of global population growth predicted to fall within urban settings (Stevens et al., 2015; Tatem and Hay, 2004), and considerable variation in age and gender composition of these populations (Alegana et al., 2015). The dynamics and distribution of these populations have crucial implications for public health applications (Alegana et al., 2015), with human population totals used to generate disease burden estimates at the global, national, and subnational scale (Hay et al., 2005). However, reliable and contemporary census and settlement data often do not exist, particularly amongst African countries (Tatem and Linard, 2011; Tatem et al., 2007). This can have important ramifications in disease outbreak, as exemplified in the case of the 2013 – 2016 Ebola outbreak in Western Africa, where emergency response was hampered by not knowing the size and locations of population settlements (Varshney et al., 2015). In the absence of such data, high-resolution population estimates can be produced using ancillary data sources available (Molla et al., 2017; Tatem et al., 2007). Historically, efforts to estimate demographic data have employed methods such as areal weighting (Tatem et al., 2007) and land-cover based redistribution (Tatem et al., 2004), while more current approaches include dasymetric redistribution (Stevens et al., 2015) and bottom-up population mapping techniques (Wardrop et al., 2018).

Areal weighting techniques constituted some of the first efforts to quantify human populations on a gridded (or raster) surface, such as the Gridded Population of the World, version 2 (Deichmann et al., 2001). These techniques consist of a simple overlay between a gridded surface, or raster surface, and an administrative polygon containing population information (such as census units), and evenly redistributing population counts to grid cells falling within the polygon of interest (Hay et al., 2005). While conceptually straightforward and easy to calculate within GIS software, these techniques critically assume a uniform distribution of population within an administrative unit (Hay et al., 2005), which is often unrealistic.

The land cover-based redistribution approach builds on the areal weighting technique to generate population estimates using ancillary satellite imagery data to map detailed layers of human settlements (Linard et al., 2012), which are then linked with census estimates to generate accurate and high-resolution population estimates. Tatem and colleagues utilized this approach in the East Africa region, combining satellite imagery data with remotely sensed land cover data to generate reproducible, adaptable estimates of populations across large geographic areas at high spatial resolutions such as 100 meters (Figure 2.16) (Tatem et al., 2007). By combining these freely available data sources such as land cover, elevation, and topography data, they demonstrated that it was possible to generate accurate estimates of human settlements and population estimates at a higher spatial resolution than any previous work. While this approach was widely scalable and flexible across low- and middle-income countries, it relied heavily on input data sources such as land cover, climate, and crucially, high-resolution census data (Tatem et al., 2007). In light of this, this approach has generally been replaced by an alternative, machine-learning algorithm such as the random forest approach (Stevens et al., 2015), which incorporates data from a wider range of ancillary data, including distance to health facilities, schools, road networks, and more.

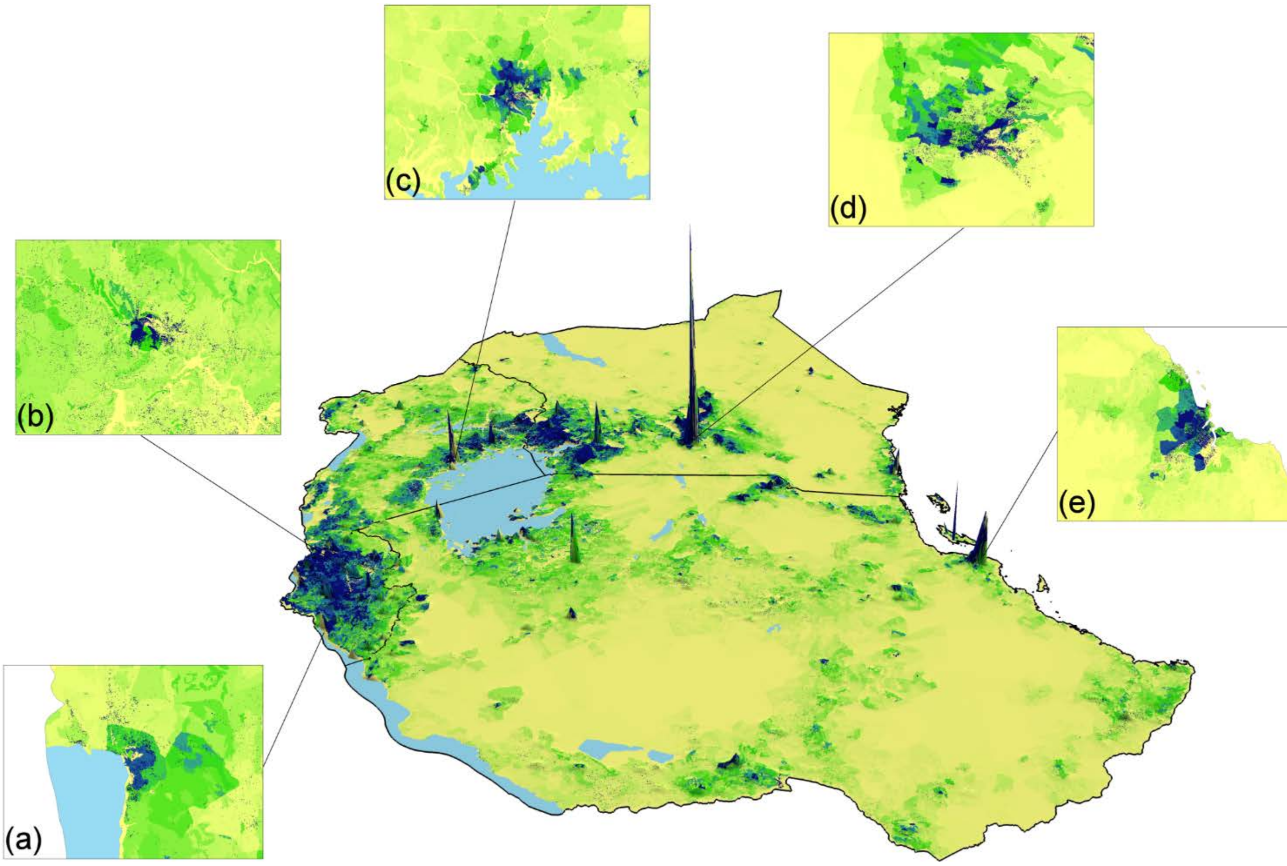


Figure 2.16. Population density of the East Africa region (Burundi, Kenya, Rwanda, Uganda, Tanzania), with selected inset cities, using a land-cover based redistribution approach, adapted from (Tatem et al., 2007)

2.2.2.2 Current approaches to mapping demographic data

Stevens et al. outline a random forest mapping technique used to disaggregate census data and generate high-resolution population estimates for Kenya, Vietnam, and Cambodia (Figure 2.17) (Stevens et al., 2015). This approach utilizes a semi-automated modelling approach, incorporating continuous global datasets, such as night-time lights, land cover and topography, as well as discrete covariates, such as distance to nearest urban area. By combining these data with census data, this approach employs dasymetric redistribution, where population counts are 'intelligently' redistributed from a coarser spatial resolution (such as census enumeration areas) to a finer spatial resolution, while preserving the total counts at the original input source (Mennis, 2003). However, instead of redistributing these population counts evenly across the finer spatial area of interest, a regression tree model (or random forest) can be used to 'unequally' distribute counts, or weight their distribution (Figure 2.18) (Stevens et al., 2015). This weighted layer contains information from a range of ancillary sources, as outlined above, and reflects underlying mechanisms contributing to unequal population distributions. This approach is robust, semi-automated and scalable, and shows improvement over more traditional mapping approaches, such as previously outlined land cover-based techniques (Stevens et al., 2015).

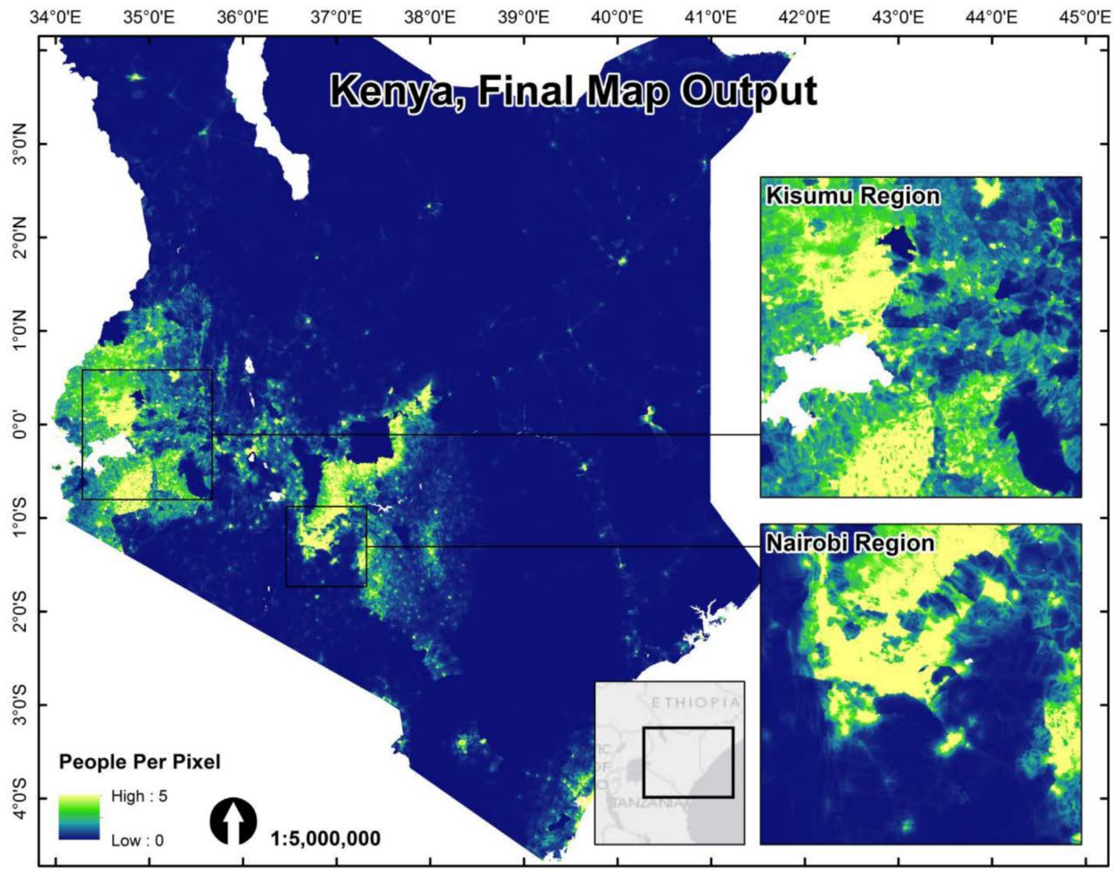


Figure 2.17. High-resolution population counts redistributed using Kenya 1999 census data and ancillary data sources (freely available at worldpop.org.uk). Adapted from (Stevens et al., 2015)

Where census data are unreliable or out of date, "bottom-up" population mapping techniques have been employed, as outlined by Wardrop and colleagues (Wardrop et al., 2018). Similar to the previous land cover-based and dasymetric redistribution techniques as outlined above, the goal of bottom-up population mapping is to generate high-resolution population estimates using a range of robust, and ideally freely available, data sources. In contrast to the above approaches (which can be considered 'top-down' population mapping), bottom-up population mapping relies on micro-census data, which collects information within smaller regions than census enumeration areas, collected at more frequent and rapid intervals (Figure 2.18) (Wardrop et al., 2018). Using statistical models to account for residual spatial autocorrelation, these micro-census population counts are linked to spatial covariates to predict population counts in un-sampled locations. Few studies have validated outputs or accuracy of these methods over other techniques such as top-down approaches, however, suggesting an emerging area for future research. Regardless, bottom-up approaches offer potential for predicting population counties in countries where census data are unreliable or sparse, offering a robust method to predict into un-sampled locations with associated model errors and uncertainty.

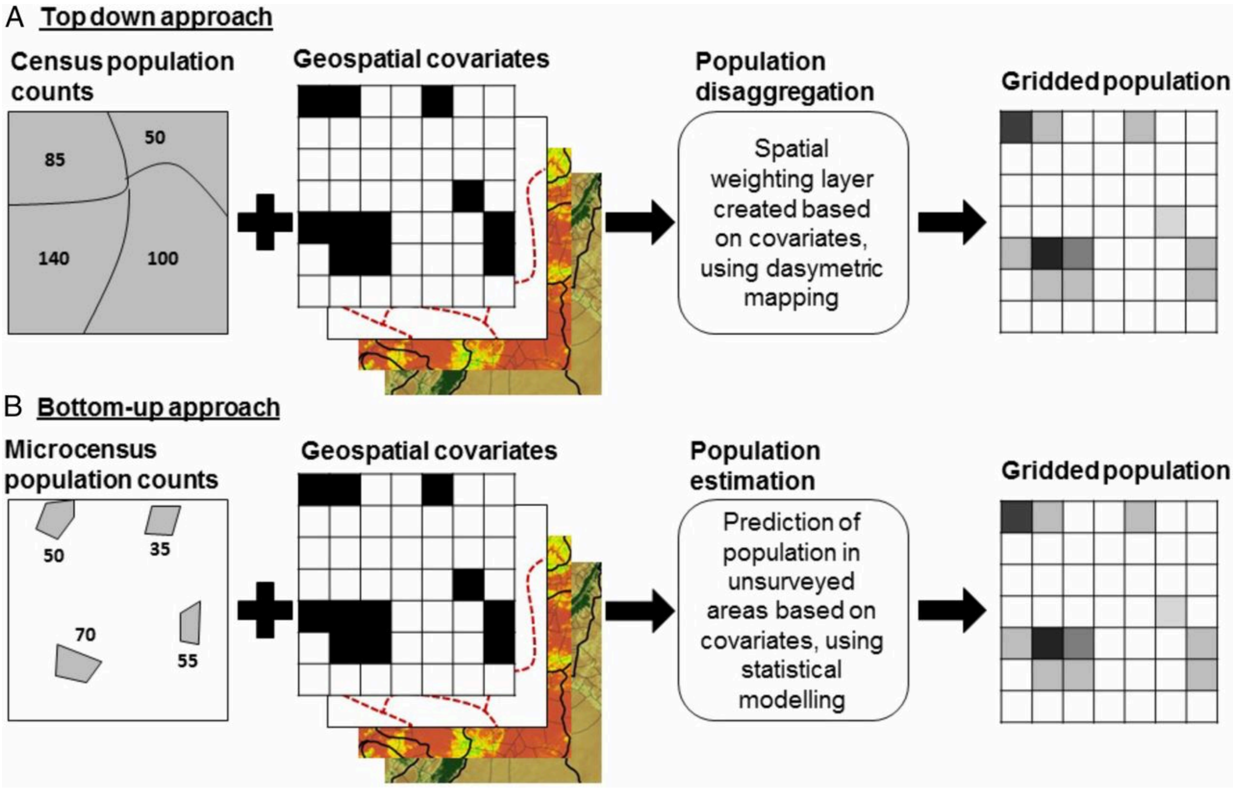


Figure 2.18. Top-down (A) versus bottom-up (B) approaches to mapping gridded populations, adapted from (Wardrop et al., 2018)

2.2.2.3 Challenges in spatial data production

Maintaining participant confidentiality, particularly when data contain sensitive health or identifying information, is a crucial consideration for any database. As spatial databases generally contain some sort of locational information, confidentiality is an important challenge, particularly amongst datasets containing highly localized movements such as call data records (CDRs) or human movement patterns (de Montjoye et al., 2013). In some cases, removing patient identifiers such as name, address, and date of birth, is a reasonable step to protecting confidentiality—however, in the case of locational coordinates (such as geo-located DHS clusters) or other spatially identifiable situations (such as CDRs), this may not be an option (Burgert et al., 2013; de Montjoye et al., 2013). Approaches exist, however, to overcome these challenges and effectively anonymize data while maintaining relevant spatial information, such as those used by Ruktanonchai and colleagues to anonymize CDR data (N. W. Ruktanonchai et al., 2016).

Working with the primary mobile phone provider across Namibia (Mobile Telecommunications Limited) representing nearly 85% of the mobile phone market, Ruktanonchai et al. obtained an anonymized dataset consisting of 1.2 million unique SIM cards in Namibia representing over 9 billion communications from October 2010 to September 2011. These data include calls or SMS text messages sent during the study period and the phone towers these events were routed through. By observing the towers used by an individual over time, the researchers were able to infer their mobility patterns. These data therefore represent sensitive and localized human movement patterns, necessitating strict confidentiality. To facilitate this, MTC removed individual SIM phone numbers and replaced them with random study numbers to be used by researchers, effectively removing any personally identifying information in the dataset. However, research has suggested that even as few as four movement data points can be used to uniquely identify up to 90% of individuals, necessitating further protocols to ensure participant confidentiality (de Montjoye et al., 2013). Towards this, Ruktanonchai et al. averaged the movement of all residents at each tower (n = 402 towers across Namibia), effectively aggregating movement data to the tower catchment level and further ensuring anonymity (N. W. Ruktanonchai et al., 2016).

Lastly, challenges unique to Africa exist in uptake of GIS technology, as outlined by (Tanser and le Sueur, 2002). Firstly, they note a lack of qualified GIS technicians and experts which prevents GIS applications from moving past the donor-initiated phase. Many health research studies in the area are funded through international donor agencies, and are often led by non-African scientists and principal investigators with sparse local engagement and contribution (Molla et al., 2019, 2017; Tanser and le Sueur, 2002). To facilitate sustainable GIS applications to address local health problems, capacity training and support must be prioritized such that local scientists who understand both cultural and health systems factors can prioritize the research agenda (Molla et al., 2019). Secondly, Tanser and le Sueur note a lack of suitable spatial datasets in addressing health and geographical research, which suffer from decentralized and uncoordinated efforts (Molla et al., 2017), in addition to time and cost constraints. They argue that cross-sector projects may help to address these challenges, creating a more unified and systematic approach to creating large spatial databases. They further argue cost-effective methods of creating these datasets include establishing large-scale sentinel demographic and health surveillance datasets. Molla et al. make similar recommendations for spatial data used in addressing maternal and newborn health questions, suggesting universal datasets should be created with common data features such as geo-coding, health facility lists, and more (Molla et al., 2017).

However, in the absence or interim of strengthening sustainable capacity strengthening efforts, it is vital to ensure that high-resolution, contemporary and reliable spatial demographic data being produced are made available to researchers across the globe. Towards this, the WorldPop project (www.worldpop.org) based at the University of Southampton works to ensure that every person is accounted for in the decision making and resource allocation process (Tatem, 2017). Fundamental to this vision is making both spatial demographic data and methods open, freely available, and transparent. The datasets available through the WorldPop project have been used not only by academic researchers across low- and middle-income countries, but also policy makers, statistical agencies, and international development agencies across the world (Howes et al., 2015; C. W. Ruktanonchai et al., 2016; N. W. Ruktanonchai et al., 2016; Sorichetta et al., 2016; Tatem, 2017; C. Edson Utazi et al., 2018b).

2.2.3 Applications in producing spatial demographic data

Despite the growing availability of spatial data, the problem of how to generate data for un-sampled locations persists. While national-level household surveys such as DHS surveys are increasingly employing geo-referencing techniques, data are often presented at the national or regional level, and may mask important inequalities at higher spatial resolutions (Bhutta ZA and Reddy K, 2012). The production of spatial demographic datasets has therefore become an increasingly recognized tool to fill in these spatial gaps by generating high-resolution surfaces of environmental covariates, population estimates, health outcomes, and more (Ebener et al., 2015). Here, I highlight case studies outlining the production and application of datasets, demonstrating how these innovative datasets can be used for cost-effective decision making and resource allocation efforts, particularly in the absence of other reliable data sources or while capacity strengthening and training efforts are ongoing.

2.2.3.1 Mapping spatial demographics

Health metrics and intervention planning often aim to target specific populations, such as family planning interventions targeted towards women of childbearing age (Alegana et al., 2015; Hay et al., 2005; A. J. Tatem et al., 2013; Tatem et al., 2014). In addition to knowing where populations are, it is therefore also vital to know who comprises these populations. Historically, however, studies mapping indicators and health risks have used statistics at the national level, and do not account for localized demographic variation and may contribute to hidden inequalities amongst the most vulnerable populations (Gwatkin, 2005; Reidpath et al., 2009; Tatem et al., 2014). Demographics such as age, gender, and estimates of births and pregnancies have important monitoring and surveillance applications, such as malaria surveillance (Alegana et al., 2015), vaccination coverage planning (C. Edson Utazi et al., 2018b), and family planning interventions (Tatem et al., 2014), amongst many others. Capturing subnational variation in these populations is therefore crucial to ensure effective resource allocation.

2.2.3.2 Age and gender composition

To quantify subnational variation in age and gender composition, Tatem et al. constructed a detailed and contemporary population dataset for the African continent incorporating information on subnational age and gender structure (A. J. Tatem et al., 2013). To do this, they compiled and collated estimates for age and gender from a range of data sources representing more than 20,000 subnational administrative units, primarily via census data, household-level microdata collected via census surveys, and census microdata. Census datasets represent the most reliable counts of age and gender, as they contain large sample sizes per small area, but other sources of data can be limited to small sample sizes, such as the case with microcensus or household survey data. In instances where microscensus or household survey data were collected within one year of census derived estimates, these were collated in order to increase sample size and reduce error. Where contemporary census data were not available, however, national household survey data were used, such as those collected through the DHS, Malaria and AIDS Indicator Surveys, and Multiple Indicator Cluster Surveys.

Proportions of individuals by age and sex were then derived from these counts, which were matched to the corresponding administrative boundary (Figure 2.19a/b). Using this Africa-wide GIS database, population estimates at the 100m resolution as produced by the AfriPop project (Linard et al., 2012) were adjusted to create a gridded dataset of distributions of populations by 5-year age groups and sex (Figure 2.19c). Additionally, these data were projected and adjusted from 2000 to 2015 at 5-year intervals by applying United Nations population growth estimates (A. J. Tatem et al., 2013).

As proof of concept, Tatem et al. further quantified how previously unaccounted for subnational demographic variation can influence important health and policy metrics, such as travel time to healthy facility and malaria transmission. By comparing these metrics generated using national level age structure data against the assembled subnational dataset described above, they found that modelled estimates could be as much as 100% discordant between each other, with as many as half of the study countries demonstrating greater than 10% discrepancies in estimates (A. J. Tatem et al., 2013). With crucial international development targets such as those associated with the Millennium Development Goals and Sustainable Development Goals tied to these estimates, in addition to national-level monitoring and surveillance funds, ensuring the accuracy of modelled estimates by capturing subnational demographic heterogeneity is vital to ensuring cost-effective decision making and policy efforts.

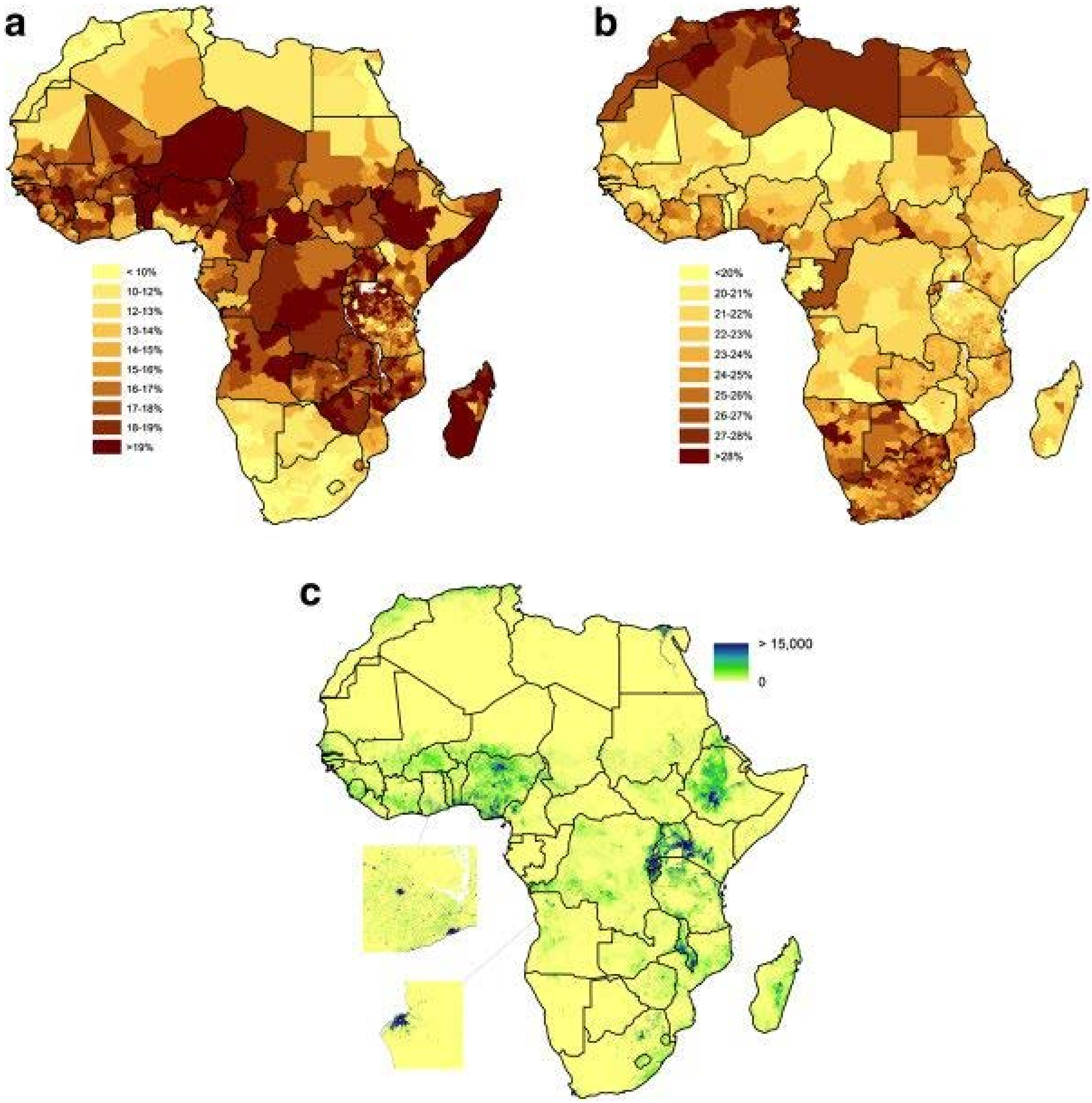


Figure 2.19. Spatial demographic datasets for Africa. A) Proportion of children under 5; B) proportion of women of child-bearing age; and, C) children under 5 in 2010 at 1km resolution. Adapted from (A. J. Tatem et al., 2013)

While this approach is useful in collating several data sources across a variety of countries, it is less useful for those countries where census data are not reliable and out of date (A. J. Tatem et al., 2013). In the absence of such data sources, Alegana et al. developed a Bayesian hierarchical spatio-temporal model based framework to integrate georeferenced household survey data (such as those collected through the DHS) with a range of spatial data to predict age and gender structure at a 1km by 1km spatial resolution in Nigeria (Alegana et al., 2015). Similar to the bottom-up population mapping approach described above (Wardrop et al., 2018), this approach links geo-located cluster surveys with ancillary satellite data such as land cover, travel time to major settlements, night-time lights, and vegetation index, to predict age structure in un-sampled locations, while statistically accounting for spatial autocorrelation.

Overall, Alegana et al. found that these freely available high-resolution datasets (namely, land cover, night-time lights, travel time to major settlements and vegetation index) were strong predictors for estimating the proportion of the population under 5 years old. Because this framework utilizes only freely available household survey data, in combination with freely available remotely sensed data, this method fills an important niche for modelling high-resolution population distributions in the absence of reliable and modern census data. This work has important ramifications in health and policy metrics, including malaria surveillance and child and maternal mortality prevention, and has been used in vaccination planning and outreach in Nigeria through the Nigeria Vaccination Tracking System (vts.econg.org) (C. Edson Utazi et al., 2018b).

2.2.3.3 Estimating live births and pregnancies

Building off previous techniques described above in mapping age and sex structure (A. J. Tatem et al., 2013), Tatem et al. produced subnational datasets depicting women of childbearing age by 5-year intervals and number of live births and pregnancies (Tatem et al., 2014). To do this, Tatem and colleagues compiled age specific fertility rates (ASFR) from national surveys such as the DHS and Multiple Indicator Cluster Survey (MICS), disaggregated by subnational region and urban versus rural rates. These ASFR estimates were then combined with data on women of childbearing age, produced via the methods outlined above, to generate gridded estimates of live births (Figure 2.20). Lastly, these estimates of live births were combined with data on abortions, stillbirths, and miscarriages provided through the Guttmacher Institute to produce estimates of pregnancies per grid cell. These outputs are crucial in planning maternal and newborn health interventions and resource allocation, and were used in the United Nations Population Division's State of the World's Midwifery report for 2014 (UNFPA et al., 2014).

The evolution of these methods form a foundation by which to explore health disparities in maternal and newborn health by quantifying where women of childbearing age, pregnant women, and newborns are. The increased availability of these data, couple with spatially explicit demographic data as collected through household surveys such as the DHS, are creating new opportunities for researchers to spatially disaggregate health outcomes and monitor progress sub-nationally (Molla et al., 2019). Towards this, spatially explicit methodologies and geospatial analysis are needed to help reduce disparities in maternal mortality and morbidity (Ebener et al., 2015; Makanga et al., 2016; Molla et al., 2019), and to ensure "no-one is left behind" in the SDG era.

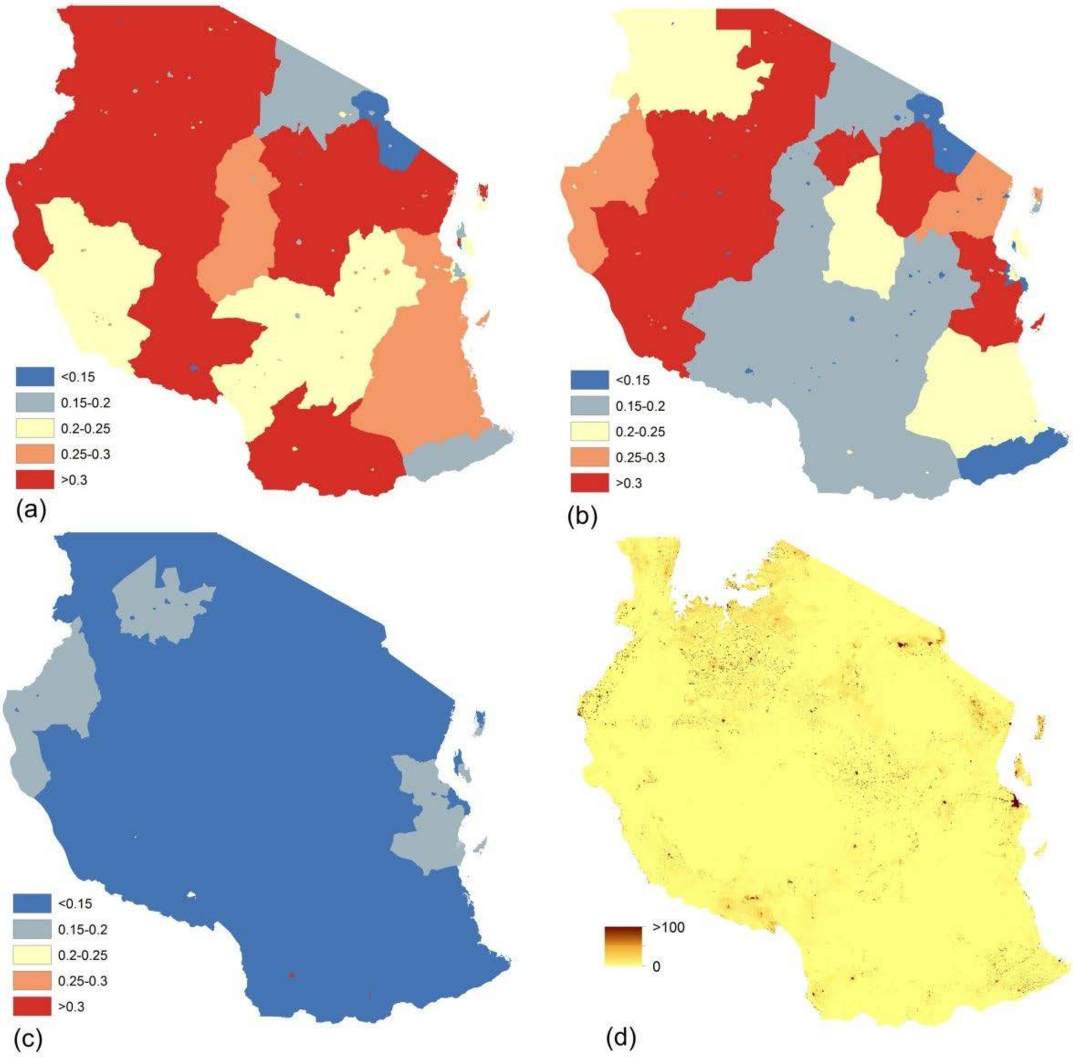


Figure 2.20. Age-specific fertility rates among those aged a) 20 - 24, b) 30 - 34, and c) 40 - 44, plus estimated live births per 100 x 100 m, Tanzania, 2012. Adapted from (Tatem et al., 2014)

2.2.4 Future directions and recommendations

Data visualization through mapping techniques represents a powerful tool for epidemiologists and demographers, particularly as the need for spatial investigation at a subnational scale becomes more prominent on the global health development agenda. Despite this, most research within public health does not incorporate spatial analysis (Auchincloss et al., 2012), and in fields such as maternal and newborn health, challenges persist in building analytic capacity among resource-poor settings (Ebener et al., 2015). Further, while several datasets exist such as census data, census microdata, and national survey data, these are scattered across disparate sources and can be difficult to obtain (Hay et al., 2005; A. J. Tatem et al., 2013), preventing comparison across time and space.

Towards this, Tatem et al. outline recommendations and future directions in improving spatial demographic datasets (Tatem et al., 2012). Firstly, they note that spatial and temporal population projections are lacking at a subnational level, even amongst international development agencies, such as the United Nations Population Division. While there are a few countries undertaking these projections at the national level, such as India and China, these projections should be scaled up to include other developing countries to allow for more accurate population estimations and resource planning. The current methods used to project these estimates, however, are subject to sources of bias and model uncertainty, which Tatem et al. note must be better quantified and communicated. While efforts to map disease risk have handled the quantification and propagation of this uncertainty through Bayesian posterior distributions (Gething et al., 2015), less research has addressed understanding and visualizing how uncertainty propagates throughout spatial demographic datasets. This uncertainty might be as a result of outdated census data or the size of input administrative units as compared to output population grid cells, for example (Tatem et al., 2012). Without accounting for these drawbacks, spatial demographic datasets and corresponding population and health metrics may be substantially limited by unquantified sources of uncertainty propagating in unpredictable ways.

Finally, there is further a need for greater analytic capacity and data resources, particularly within resource poor settings (Ebener et al., 2015; Molla et al., 2017). Molla et al. outline future directions and policy recommendations for improving the use of GIS within the field of maternal and newborn health, but with broader applications towards health policy in developing countries. They categorize challenges and recommendations into three broad themes: 1) ancillary geospatial and maternal and newborn health data sources; 2) technical and human resources needs; and, 3) community participation (Molla et al., 2017). Noting that while GIS holds substantial potential in reducing the number of preventable maternal and child deaths, reaching this potential will require high quality spatial data and improving current health systems data, such as vital registration statistics and standardized disease surveillance systems (Rushton, 2003). This will require a quality improvement cycle for georeferenced data, integration of data from both the public and private domain, community involvement in participatory mapping efforts to enhance spatial data infrastructures, and finally, regular monitoring and evaluation of inequities in tandem with collaboration from policy makers. Building in-country technical capacity to perform these tasks will be crucial in ensuring recommendations are implemented and in-country policy needs are met, which in turn will support efforts to end preventable deaths among women and children (Molla et al., 2017).

Chapter 3: Study framework

To understand where women and children are dying, why they are dying, and what factors are driving these inequitable deaths, studies synthesizing geography, maternal health, and health inequalities are needed. This work aims to combine methodologies outlined in previous sections to address this need, producing high-resolution estimates of inequalities in utilisation of maternal and newborn health services, and how these inequalities have evolved over time in the East African Community region. Here, this chapter outlines the overall framework for the three studies comprising this work, including a conceptual framework, followed by detailed research questions and hypotheses for each of the studies. A study justification is outlined for 1) study indicators used, 2) the study area of interest, and 3) study methods used to address research questions. Finally, this chapter concludes by outlining scientific contributions and impact this work makes, along with intellectual contributions made for each substantive chapter.

3.1 Conceptual framework

Figure 3.1 applies a monitoring and evaluation framework to outline selected national-level structural policies and regulations, facility-level processes and inputs, individual-level outcomes and indicators and resulting impact. This study will incorporate individual-level outcomes throughout its analyses, which are broadly influenced by: 1) national-level structural elements, such as national policies relating to maternal deaths notification and maternal health expenditure, the number of women represented in national parliamentary bodies and quality of national health information systems; and, 2) facility-level process and inputs, such as the percent of minimum recommended facilities offering basic and comprehensive EmONC services, the percent of women of childbearing age living within a 2-hour travel time of an emergency care facility and quality of care and satisfaction with services provided. The focus of the analyses in the following chapters therefore comprise factors influencing individual-level outcomes and indicators, including antenatal care, skilled birth attendance, postnatal care, and delivery via caesarean section (c-section).

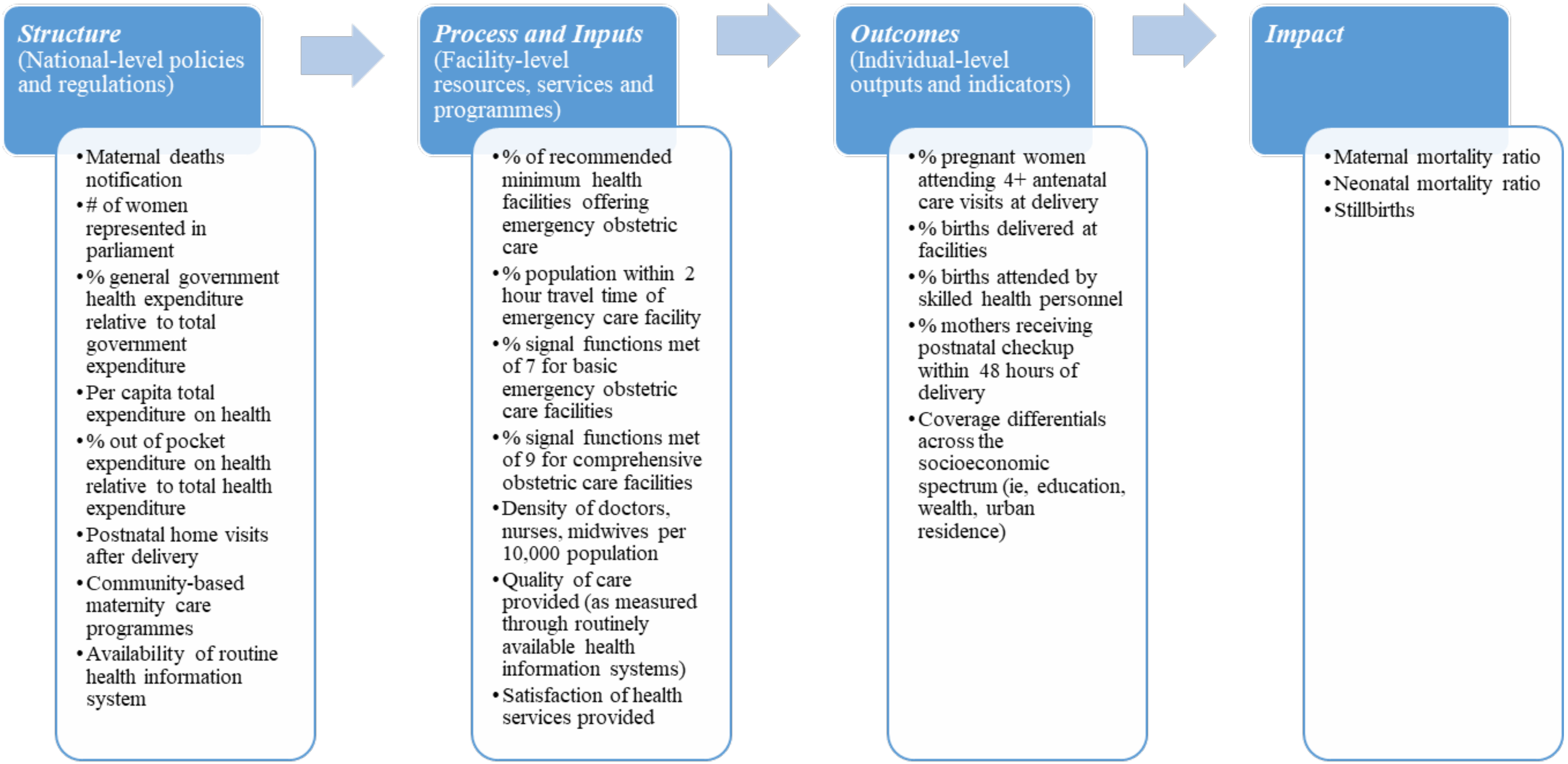


Figure 3.1 Study framework for monitoring and evaluating maternal and newborn health care utilisation

3.2 Research questions

3.2.1 Chapter 4 research questions

Chapter 4, entitled *Equality in Maternal and Newborn Health: Modelling Geographic Disparities in Utilisation of Care in Five East African Countries*, examines several MNH outcomes in the context of geographic accessibility to map the likelihood of receiving care before, during, and after delivery. To do this, I utilise a geo-referenced dataset of nearly 10,000 health facilities to generate high-resolution surfaces and administratively relevant maps reflecting the probability of a woman obtaining critical MNH care throughout the five East African Community partner states. Specifically, I produce high-resolution, disaggregated estimates of probability of MNH utilisation as a function of geographic accessibility. These findings have important policy implications for focusing future intervention efforts and allocation of resources, as well as providing a baseline from which to monitor future progress in the SDG era. Within this study I aim to address the following research questions:

1. What are the primary drivers of utilisation of antenatal care, skilled birth attendance, and postnatal care within the East African Community study region?
    a. Does geographic accessibility to a health facility predict utilisation of these services, and does this vary by service utilised (i.e., ANC, SBA, versus PNC)?
2. Provided current health facility locations throughout the study region, where are women most likely to utilise these MNH services at both a high-resolution (300 x 300 m) scale and policy-relevant scale (administrative level II)?

3.2.2 Chapter 5 research questions

While Chapter 4 examines utilisation of MNH care as predicted by geographic accessibility, Chapter 5, entitled *Temporal trends in spatial inequalities of maternal and newborn outcomes among four East African countries, 1999 – 2015*, examines how these spatial inequalities have evolved over time. Here, this study builds upon the previous chapter to analyse sub-nationally where spatial inequalities in coverage of vital MNH services have improved, stayed the same, or grown wider within the EAC region. Specifically, I employ a Bayesian inference framework to spatially interpolate coverage estimates for antenatal care, skilled birth attendance, and postnatal care at the administrative II level throughout the study countries at multiple time points using DHS data. I report both absolute and relative indices of change by visualizing the absolute difference between the first and last survey points available for these estimates, and reporting relative performance ratios between the best and worst performing sub-national units for each country. Lastly, I present logistic regression coefficient plots for the best versus worst performing region among each survey time point available, reflecting the extent to which spatial inequality is occurring as well as its evolution over time. Specifically, within this study I aim to address the following research questions:

1. How has coverage in SBA, ANC, and PNC within study countries changed absolutely over time, by administrative unit II?
    a. Which administrative units have had the most improvement in coverage? Which have had the least improvement?
2. How does the change in coverage among these administrative units compare relative to each other?
    a. How wide is the change-in-coverage gap between administrative units within a country?
    b. Has this change-in-coverage gap improved over time, gotten worse, or stayed the same?

3.2.3 Chapter 6 research questions

Chapter 6, entitled *Estimating uncertainty in geospatial modelling at multiple spatial resolutions: the pattern of delivery via caesarean section in Tanzania*, aims to explore the trade-off between modelled estimates of delivery via c-section in Tanzania and associated uncertainty at increasing spatial resolutions within a Bayesian framework. To do this, I predict prevalence of delivery via c-section at the 5km, 50km, and 100km scales, implemented via a stochastic partial differential equation (SPDE) approach utilising the Integrated Nested Laplace Approximation (INLA) technique within the R-INLA package (Rue et al., 2009). I explore the posterior distribution and fit of these models, and visualise estimates and uncertainty at these spatial resolutions. Specifically, within this chapter I aim to address the following research questions:

1. What is the trade-off between increasing spatial resolution and model fit?
    a. How does the overall posterior distribution of the 95% credible interval change with increasing spatial resolution?
2. How does uncertainty in estimates of prevalence of delivery via c-section propagate spatially across the landscape at varying resolution sizes?
    a. Are there areas with consistently high or low estimates of delivery via c-section across spatial resolutions?
    b. Are there areas with consistently high or low uncertainty across spatial resolutions?

3.3 Study indicators

3.3.1 Antenatal care

Routine antenatal care appointments are critical to identifying risks, preventing and managing complications, and educating and promoting health throughout pregnancy to ensure a safe delivery (Bloom et al., 1999; World Health Organization, 2016a). Through routine monitoring and contact of pregnant women, maternal and perinatal mortality is reduced both directly and indirectly: firstly, through detection and management of complications occurring in pregnancy, labour, and delivery; and secondly, through prevention and management of simultaneous disease, such as malaria and HIV. While utilisation of ANC has increased in low and middle-income countries since 2002, less than two-thirds of women obtained the recommended 4 or more ANC visits between 2007 and 2014 (World Health Organization, 2016a). Further, since that time the WHO has increased the number of recommended ANC contacts to eight, based on evidence suggesting the four-visit model did not adequately reduce perinatal mortality or improve women’s satisfaction with the quality of care obtained (World Health Organization, 2016a). This suggests even fewer women are obtaining the required number of 8+ ANC contacts.

Many social, cultural, and geographical factors influence the decision and extent to which a woman will obtain the recommended number of antenatal care (ANC) visits, however. Simkhada and colleagues aimed to identify these barriers, performing a literature review to examine the critical determinants of predicting ANC coverage across the socioeconomic spectrum, specifically within the context of developing countries (Simkhada et al., 2008). Among twenty-eight studies, they found a variety of social, political and economic factors such as education, income, marital status, a history of complications, and supply-side factors including cost and availability, to be important predictors of ANC utilisation. More recently, Saad-Haddad performed a cross-country analysis exploring determinants of ANC utilisation throughout seven Countdown Initiative countries, similarly finding large disparities in obtaining 4+ ANC visits by household wealth, woman’s education, and place of residence (Saad–Haddad et al., 2016). Further, conducting a systematic literature review of twenty-one qualitative studies among low and middle-income countries, Finlayson and Downe (2013) identified emergent themes in women’s experiences as to why they did not obtain or utilise antenatal care services. These primarily included reasons surrounding: i) pregnancy perceived as a ‘normal life event’ (e.g., only attending ANC appointments when unwell); ii) lack of necessary resources (e.g., transportation and other associated costs, time off work or childcare, or inadequate infrastructure); and, iii) poor prior experiences (e.g., supply-side factors such as lack of staff, long waiting times, or disrespectful care) (Finlayson and Downe, 2013).

Importantly, Simkhada et al. noted that geographic accessibility was a key driver in obtaining antenatal care, comprised of determinants such as place of residence, distant to healthcare facilities, and type of transport available. Specifically, women in urban areas were generally found to be at higher odds of obtaining ANC as compared to those in more rural settings, and were found to be more likely to obtain ANC from a skilled health provider, in line with later findings by Saad-Haddad and colleagues (Saad–Haddad et al., 2016). Further, Simkhada et al. found that increasing distance to health facilities was significantly associated with fewer ANC contacts, supported by both quantitative and qualitative findings (Finlayson and Downe, 2013; Saad–Haddad et al., 2016;

Simkhada et al., 2008). Lastly, they noted that the type of geography encountered was a barrier to obtaining ANC, including poor road conditions, uncomfortable and crowded public transport, and inability to cross major bodies of water (Simkhada et al., 2008).

In addition to these findings, Kyei et al. examined the effect of distance to health facility on number and timing of ANC visits in rural settings within Zambia, finding that increasing distance to the nearest health facility strongly influenced the quality of care a woman received (Kyei et al., 2012). These findings suggest that geography is an important barrier in both the quality and quantity of ANC visits that a woman obtains, yet varies drastically by the social and cultural factors specific to each country. Country and region-specific analyses incorporating geospatial approaches are therefore critical in improving the utilisation of and satisfaction with antenatal care contacts.

3.3.2 Skilled birth attendance

Skilled birth attendance (SBA), along with antenatal care, continues to be a key driver of maternal and newborn mortality with persisting inequalities (WHO, 2015a). As most life-threatening complications occur around the time of labour and delivery, it is vital for women in labour to be monitored by an attendant trained in the identification and management of obstetric emergencies. This is evidenced by the inclusion of coverage of skilled birth attendance in both Millennium Development Goal and Sustainable Development Goal indicators (Table 2.1), and has been identified by the World Health Organisation as one of the "single most important factor(s) in preventing maternal deaths" (World Health Organization, 1999).

Globally, over 80% of births were attended by skilled health personnel, yet while skilled birth attendance in Sub-Saharan Africa increased over 2012 to 2017, just over 50% of births were attended by a skilled health professional (World Health Organization, 2018a), suggesting barriers remain in the utilisation and uptake of skilled attendance at birth. Despite its importance as a key intervention in preventing maternal and newborn deaths, disparities in skilled birth attendance both between and within low- and middle-income countries persist (Gwatkin et al., 2007; WHO, 2010b, 2015a). SBA as a maternal health intervention has further been identified as having the most pronounced economic inequalities (Gwatkin et al., 2007), in line with the "inverse care law" suggesting that the poorest populations in greatest need of health services often receive the fewest services (Kruk et al., 2008; Victora et al., 2003). Towards this, Kruk and colleagues explored SBA utilization among 45 countries with DHS surveys, finding that governmental policies focused on ensuring primary education for all can have a marked effect in increasing skilled attendance at delivery (Kruk et al., 2008). These results suggest that a woman's education is a primary driver in utilising skilled birth attendance, in line with findings among other studies across low- and middle-income countries (Gitimu et al., 2015; Hazarika, 2011; Mpembeni et al., 2007; Yanagisawa et al., 2006).

In their systematic literature review, Gabrysch and Campbell further identified twenty key determinants predicting utilisation of SBA, and grouped them into four major themes, including sociocultural factors, perceived benefit/need, economic accessibility, and finally, physical accessibility (Gabrysch and Campbell, 2009a). Specifically, among 80 original articles and 2 reviews, they found common sociocultural determinants, such as age, parity, education, income, and urban residence to be key in predicting use of SBA during delivery. Importantly, they note that the majority of studies tended to focus on these socioeconomic variables, while neglecting variables related to physical accessibility and qualitative measures of perceived need. Among those studies examining physical accessibility and need, they found distance to health facilities and quality of care received to be influential in facilitating health service use during delivery. Their findings ultimately suggest that future analyses of SBA must critically explore physical and geographic accessibility measures to fully understand the use of skilled birth attendance and health facility use, and ultimately reduce the inequalities persisting amongst these subgroups.

3.3.3 Postnatal care

The hours, days, and months following delivery also represent a crucial time for both women and newborns alike. Half of all postnatal maternal deaths occur within the first week of delivery, with the majority occurring in the first 24 hours of birth; similarly, the majority of newborn deaths occur in the first days and week of life (The Partnership for Maternal, Newborn and Child Health, 2006). Yet while the majority of deaths occur in this timeframe, the PMNCH has identified interventions targeted on this period as among “the weakest of all reproductive and child health programmes in the region” (The Partnership for Maternal, Newborn and Child Health, 2006). Indeed, it is a period that is often characterized by poor quality of care or an absence of care entirely, and is poorly researched (World Health Organization and Department of Maternal, 2013).

Unsurprisingly, fewer studies have examined the effects and determinants of postnatal care (PNC), despite its potential to reduce global maternal and newborn deaths. However, among studies exploring key drivers of postnatal care, similar socioeconomic characteristics arise as those described for ANC and SBA. For example, Dahiru and Oche (2015) explored utilisation of ANC, SBA and PNC in Nigeria, finding education, place of residence, and wealth to be consistent predictors of health service utilisation (Dahiru and Oche, 2015). These findings were echoed by Somefun and Ibisomi (2016), who also explored PNC utilisation among women in Nigeria, finding ANC use, distance to facility, education, place of delivery/skilled attendance at delivery, geographic region and wealth to be important predictors of PNC services (Somefun and Ibisomi, 2016). These results are generalizable to other low- and middle-income countries, where similar factors including ANC use, skilled birth attendance, education, wealth, and distance to facility were found to be key compositional factors for women in Kenya (Akunga et al., 2014), Tanzania (Mohan et al., 2015) and Bangladesh (Islam MR and Odland JO, 2011).

While no systematic literature review has been undertaken examining predictors of PNC utilisation, Fort and colleagues undertook a comprehensive analysis to explore the occurrence, timing, and characteristics associated with utilising PNC throughout 30 developing countries using DHS data (Fort et al., 2006). Their findings showed that as much as 70% of women giving birth in these countries do not receive adequate postnatal care, with the average timing of PNC among non-institutional deliveries around 3 days after birth. Compositional characteristics associated with utilisation of PNC included wealth, education, urban residence and receipt of ANC prior to birth. These findings are in line with characteristics associated with both ANC and SBA, suggesting that these outcomes are tightly correlated with each other (Akunga et al., 2014; Dahiru and Oche, 2015; Islam MR and Odland JO, 2011; Somefun and Ibisomi, 2016). Ultimately, this suggests that an understanding of more generalized health service utilisation patterns might be an effective approach to increasing service utilisation among all three interventions (Dahiru and Oche, 2015).

The commonalities among these compositional factors suggest they are critical in understanding the factors influencing the utilisation of ANC, SBA and PNC. This understanding can then be applied to identify vulnerable subpopulations for disaggregated analysis. However, the use of these services continues to be unequally distributed. Specifically, the WHO found that while many vulnerable countries made overall progress in key intervention coverages, many inequalities persisted as a result of economic subgroups, including those with less education and wealth (WHO, 2015a). Notably, antenatal care and skilled birth attendance continue to have the greatest socioeconomic inequalities, suggesting an urgent need for disaggregated analysis to identify vulnerable subgroups and targeted interventions (Barros et al., 2012; WHO, 2015a).

3.3.4 Delivery via caesarean section

Rates of caesarean sections (c-section) performed around the world have seen an unprecedented rise over the several few decades across all WHO regions, yet these rates show vast differences in the degree of incline based on high-income versus low- and middle-income countries (Betrán et al., 2007). The optimal rate at which c-sections should be performed remains controversial, with the WHO suggesting rates higher than 10 – 15% were ‘unjustifiable’ in the mid 1980’s (World Health Organization, 1985). Yet while delivery via c-section can save the life of both woman and child when medically indicated, it can conversely pose otherwise unnecessary risks in both the long and short term (Sandall et al., 2018). The variability of c-section rates by country reflects this, with strategies in high-income countries focusing on the reduction of unnecessary c-section, and strategies in low- and middle-income countries focusing on increasing the accessibility and availability of emergency c-section procedures (Betrán et al., 2007). Within African settings, the rate of delivery via c-section has increased since 2010, but remains the lowest WHO region to perform the procedure, at around 10% of births being performed via c-section in 2015, with rates as small as 0.6% in South Sudan (Wise, 2018). Crucially, delivery via c-section remains a vital and life-saving emergency procedure among low-income countries, strongly correlated with decreasing maternal and newborn deaths, with c-section rates below 10% suggesting that the most vulnerable pregnant women are not getting adequate care (Althabe et al., 2006).

Within resource-poor settings, medically indicated c-sections frequently do not occur largely as a result of barriers including accessibility, availability, and acceptability of care (Betrán et al., 2007; Wise, 2018). Irani and Deering explored challenges affecting accessibility to c-section procedures where medically indicated, performing a systematic review comprising 19 studies throughout 16 Sub-Saharan African countries. They found the average rate of c-section delivery was 3.6%, ranging from 1.5% to 7.1%, and reported major barriers to care including poverty, accessibility to care, and shortage of skilled healthcare personnel (Irani and Deering, 2015). Specifically, they noted that the number and availability of trained healthcare providers and facilities offering 24-hour coverage posed a significant challenge throughout the region, particularly amongst rural areas. Further, poverty was found to be an important barrier to uptake and utilisation of necessary c-section delivery, as many facilities would not provide care until the necessary fees had been paid.

In addition to these availability barriers, they noted accessibility barriers such as poor road conditions, poor transportation infrastructure such as emergency vehicles, inadequate public transportation systems, and long distances to health facilities capable of providing the procedure. They note that these geographic barriers are crucial barriers in obtaining appropriate surgical care, attributing between 88% to 99% of maternal deaths as preventable if women were able to reach emergency obstetric care within a timely manner (Irani and Deering, 2015; Knight et al., 2013; Maternal Health and Safe Motherhood Programme, 1996). These barriers mirror those encountered when obtaining other key MNH services, including ANC, SBA, and PNC, suggesting that a woman’s geographical and environmental context can play a critical role in life or death when encountering obstetric emergencies.

3.4 Study area

Inequalities in access to MNH services such as antenatal care, postnatal care, skilled attendance at delivery, and delivery via c-section persist not only on the global level, but within regions, as well. Within sub-Saharan Africa, the Eastern Africa sub-region as defined by the UN MDG groupings saw the greatest reduction in MMR between 1990 and 2015, with a 57% overall change and 3.4% average annual change (WHO et al., 2015). However, this overall reduction masks heterogeneity within even this sub-region, with the countries falling in the East African Community region (comprised in 2015 of Burundi, Kenya, Rwanda, Tanzania, and Uganda, with the addition of South Sudan in 2016) seeing varying amounts of improvements over the past two decades. The EAC region (as it stood in 2015 when these analyses began) therefore represents a relevant sample of sub-Saharan African countries ideal for exploring variation in utilisation of maternal and newborn care services, comprised of both countries that have both achieved MDG targets, as well as those with persistently high rates of maternal mortality.

3.4.1 Burundi

Figure 3.2 shows the distribution of women of childbearing age in Burundi for the year 2015, using data obtained from WorldPop (www.worldpop.org). Burundi had an estimated 488,000 births in 2015, with a total 3,400 maternal deaths in 2013 and a lifetime risk of maternal death at 1 in 22. In 1990, the country had an MMR of 1220 maternal deaths per 100,000 live births, representing one of the highest in the region, behind only Rwanda (WHO et al., 2015). In 2015, this number had been reduced to 712 maternal deaths per 100,000 live births, with an overall 41.6% reduction in MMR and 2.2% average annual change. These estimates suggest that Burundi has made insufficient progress towards meeting MDG target 5a of 75% reduction in MMR, as the reduction was under greater than 25% but less than 50% (WHO et al., 2015). Using 2010 DHS data, only 1 in 3 women living in Burundi were estimated to have obtained 4+ ANC visits regardless of socioeconomic status, with even less women receiving a postnatal visit within 2 days (30%). Further, less than 2 in 3 women (60%) were estimated to have births attended by a skilled health professional, with wide gaps observed between the poorest and richest quintiles (UNICEF and WHO, 2015; WHO, 2016b). Lastly, only 4% of births between 2005 to 2010 were delivered via c-section (World Health Organization, 2018b).

While having policies in place to ensure postnatal home visits within the first week of birth, Burundi represented the only country among the EAC region to lack a fully costed national implementation plan for maternal, newborn and child health as of 2015. Further, there were no laws or regulations allowing for adolescents to access contraceptives without parental or spousal consent, and no maternal deaths notification system. The density of health workers per 10,000 population was 2.2 in 2004, and met only 27% of the recommended minimum number of Emergency Obstetric Care facilities in 2010(UNICEF and WHO, 2015). These suggest that Burundi’s policies, health systems, and financing are lacking for women and newborns, with much progress left to be made.

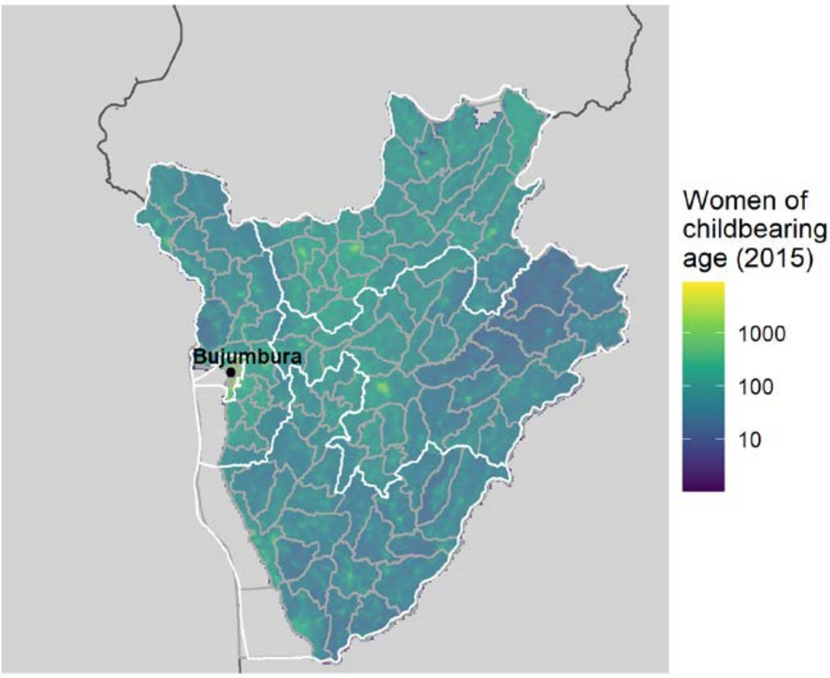


Figure 3.2. Distribution of women of childbearing age in Burundi, 2015. White lines delineate 2010 DHS boundaries, while grey lines delineate administrative II units.

3.4.2 Kenya

Figure 3.3 shows the distribution of women of childbearing age in Kenya for the year 2015, using data obtained from WorldPop (www.worldpop.org). In 2015, Kenya had 1,571,000 births with a total of 6,300 maternal deaths in 2013 and a lifetime risk maternal death at 1 in 53. While Kenya started with fewer maternal deaths per 100,000 live births, it has seen very little progress in reducing its MMR since 1990, designated as ‘No progress’ towards achieving MDG 5a (WHO et al., 2015). There has been a total reduction of 26% from 687 deaths in 1990 to 510 deaths in 2015, representing an average annual reduction of 1.2%. However, it is important to note this point estimate falls within an 80% uncertainty interval suggesting these numbers could have actually increased per year (lower estimate: -0.5%, upper estimate: 2.8%). Other services, however, such as antenatal care and postnatal care received were higher than neighbouring Burundi, with just over half of women receiving a postnatal visit within 2 days and nearly 60% receiving the recommended number of antenatal care visits. Skilled birth attendance during delivery, however, remained comparable to Burundi, at 62%, with equally high gaps of inequality observed between the poorest and richest households (UNICEF and WHO, 2015; WHO, 2016b). Finally, Kenya represented the country with the largest proportion of recommended minimum number of emergency obstetric care services available at over 50%, as compared to proportions between 25% - 35% for the rest of the region (UNICEF and WHO, 2015). This translated into 8.7% of births in 2009 delivered via c-section, over twice the proportion observed for Burundi (World Health Organization, 2018b).

Kenya has a fully costed implementation plan in place, including other health systems and financing, to protect the health of women and their newborns. As of 2015, the country had laws and regulations allowing adolescents to access contraceptives without spousal or parental consent, as well as a national maternal deaths notification system in place. Further, there were several policies in place aimed at preventing complications/mortality, including Kangaroo Care for low-weight or preterm babies, antenatal corticosteroids as routine management of preterm labour, and postnatal home visits within the first week of birth. The density of health workers per 10,000 population was just over 10 in 2013, yet in 2003, the country had met only 54% of the recommended EmONC facilities for the country (UNICEF and WHO, 2015). Together these policies suggest Kenya has prioritized maternal and newborn health, but a gap exists in implementing these into actual deaths prevented, with the third highest lifetime risk of dying in childbirth in the region.

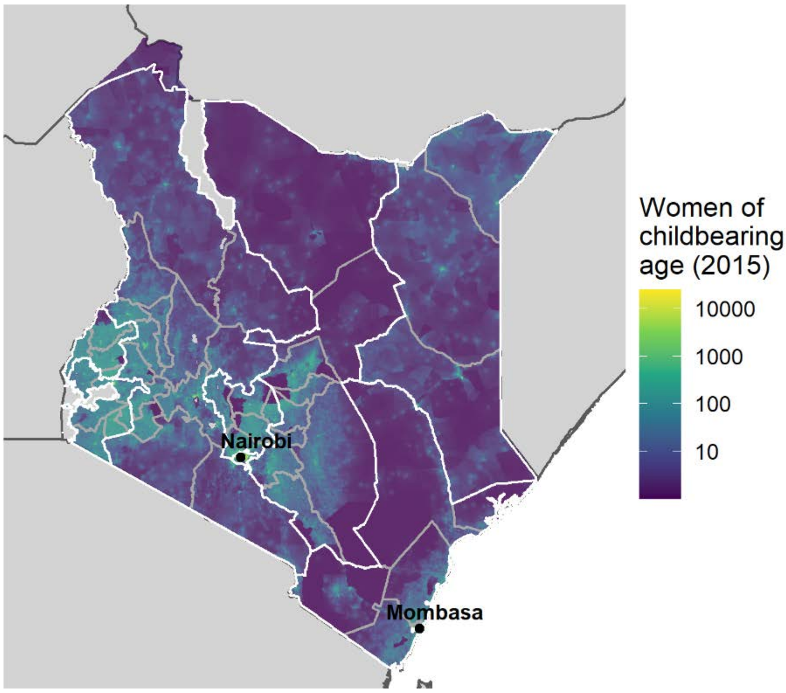


Figure 3.3. Distribution of women of childbearing age in Kenya, 2015. White lines delineate 2014 DHS boundaries, while grey lines delineate administrative II units (as of 2013).

3.4.3 Rwanda

Figure 3.4 shows the distribution of women of childbearing age in Rwanda for the year 2015, using data obtained from WorldPop (www.worldpop.org). Rwanda had 363,000 births in 2015 with a total of 1,300 deaths in 2013 and a lifetime risk of death due to maternity at 1 in 66. Among one of only four countries, Rwanda successfully achieved the MDG 5a target of reducing the maternal mortality ratio by 75%. In 1990, Rwanda's MMR was the highest among the five EAC countries at 1300 per 100,000 births. In 2015, this number fell to less than 300, representing a nearly 78% reduction and an average annual percent reduction of 6% (WHO et al., 2015). In addition to achieving this reduction in MMR, skilled attendance at birth increased substantially, from 26% of births attended by skilled health personnel in 1992 to over 90% in 2014/2015, according to DHS data. This represented the highest overall skilled birth attendance in the region. However, these estimates were still subject to gaps in socioeconomic status, with skilled birth attendance coverage among poorer households around 60%. Despite progress in increasing skilled birth attendance and reducing MMR, obtaining recommended antenatal care and postnatal remained low, at 44% and 42%, respectively (UNICEF and WHO, 2015). Lastly, Rwanda had the highest proportion of births delivered by c-section in the region at 13.0% between 2010 and 2015 (World Health Organization, 2018b).

While not having laws or regulations allowing adolescents to access contraceptives without parental or spousal consent, Rwanda did have a fully costed maternal, newborn, and child health implementation plan in place, a routine maternal deaths notification as of 2015, and policies ensuring postnatal home visits within a week of birth, use of antenatal corticosteroids in preterm management, and Kangaroo Care for preterm/low-weight births. The density of health workers per 10,000 was slightly less than Kenya, however, with 7.5 as of 2010, and meeting only 35% of the recommended EmONC facilities in 2007 (UNICEF and WHO, 2015). While there is progress to be made in terms of strengthening policies and health systems, Rwanda remained the only country within the EAC community to achieve the MDG5a target, suggesting they have prioritized maternal and newborn health over the previous years.

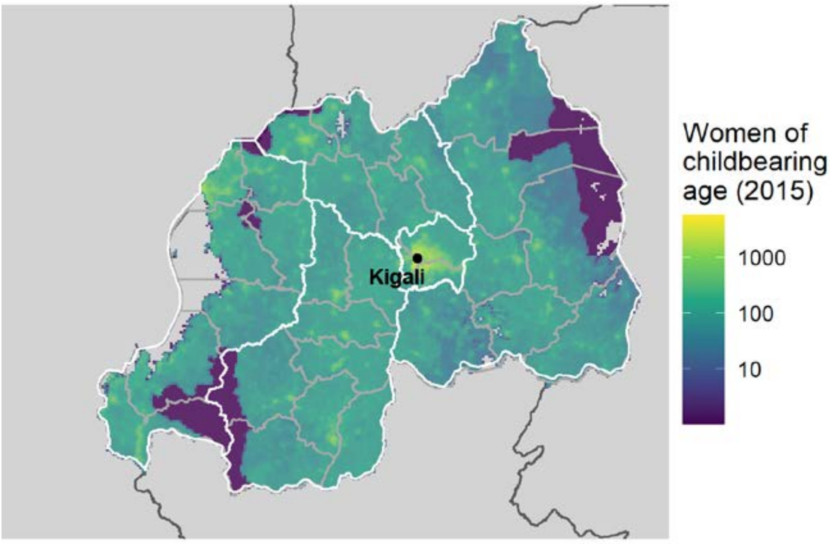


Figure 3.4. Distribution of women of childbearing age in Rwanda, 2015. White lines delineate 2015 DHS boundaries, while grey lines delineate administrative II units.

3.4.4 Tanzania

Figure 3.5 shows the distribution of women of childbearing age in Tanzania for the year 2015, using data obtained from WorldPop (www.worldpop.org). Tanzania saw a total of 7,900 maternal deaths in 2013 among over 2 million births in 2015, with a lifetime risk of maternal death at 1 in 44. In 1990, the country recorded an MMR at just under 1,000 deaths per 100,000, which fell to the just under 400 in 2015. This therefore represented a reduction of approximately 60% with an average annual reduction rate of 3.7%, marking the country as ‘making progress’ towards achieving MDG 5a (WHO et al., 2015). Wide gaps were again observed among skilled birth attendance between the wealthiest and poorest households using the 2010 DHS, with only 1 in 3 of the poorest women having skilled attendance at delivery, as compared to over 90% of the richest. Under half of women in the country obtained 4+ ANC visits, with less than 1 in 3 obtaining a postnatal visit 2 days after birth (UNICEF and WHO, 2015). Lastly, only 5.9% of births between 2010 and 2016 were delivered via c-section (World Health Organization, 2018b).

Tanzania’s health policies and systems are similar to that of Kenya, with a fully costed national implementation plan for maternal, newborn and child health, as well as laws protecting adolescent accessibility to contraceptives without other’s consent. While Tanzania did not have routine antenatal corticosteroid management for preterm labour, the country did ensure Kangaroo Care for preterm/low-weight births, and postnatal home visits within a week of birth. The density of health workers, however, was unacceptably low at only 4.7 doctors, nurses and midwives per 10,000 population, and the country met only 21% of the minimum recommended number of EmONC facilities as of 2005 (UNICEF and WHO, 2015). This suggests that while Tanzania has in place several encouraging policies, health systems and financing could be strengthened.

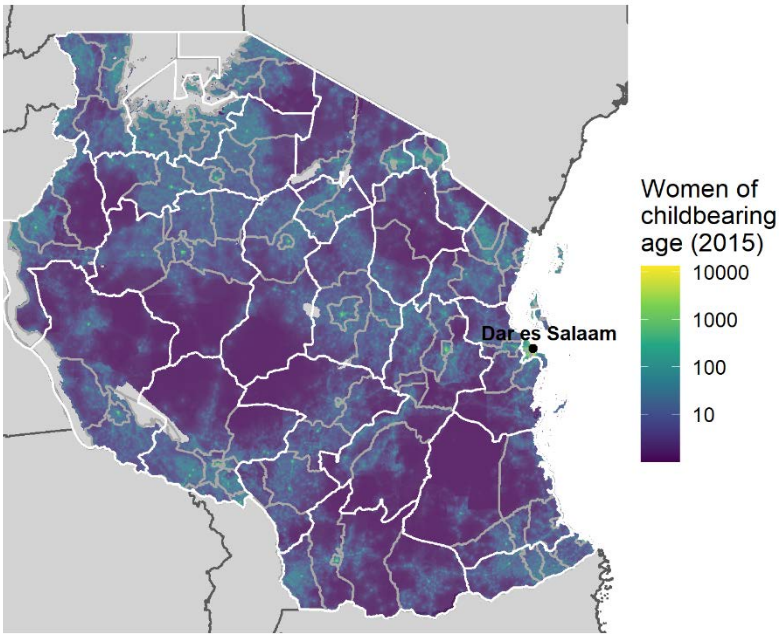


Figure 3.5. Distribution of women of childbearing age in Tanzania, 2015. White lines delineate 2015 DHS boundaries, while grey lines delineate administrative II units.

3.4.5 Uganda

Figure 3.6 shows the distribution of women of childbearing age in Uganda for the year 2015, using data obtained from WorldPop (www.worldpop.org). Uganda had 1,665,000 births in 2015 with a total of 5,900 deaths in 2013 and a lifetime risk of maternal death at 1 in 44, similar to Tanzania. Also consistent with Tanzania, Uganda was marked as 'making progress' towards achieving MDG 5a, with a reduction of just over 50% in MMR from 687 deaths per 100,000 in 1990 to 343 deaths in 2015, representing an average decline of almost 3%. Consistent with the entirety of the EAC region, skilled attendance presented some of the widest inequalities in maternal health indicators, with around 40% of women in the poorest household receiving skilled birth attendance, as compared to almost 95% of the richest households. In 2011, just under half of women surveyed in the DHS interview had obtained 4+ ANC visits, while 1 in 3 had obtained a postnatal visit 2 days after delivery (UNICEF and WHO, 2015). Lastly, Uganda had similar rates of delivery via c-section as Tanzania and Burundi, with only 5.3% of births between 2006 and 2011 delivered via c-section (World Health Organization, 2018b).

Uganda's policies for promoting maternal and newborn health varied, with a fully costed national implementation plan for maternal, newborn and child health, but only partial regulations protecting adolescents' ability to access contraceptives without parental or spousal consent. Further, while postnatal home visits and Kangaroo Care for preterm/low-weight babies were routine, there were no laws as of 2015 promoting use of antenatal corticosteroids for preterm management. However, the density of health workers was highest in Uganda as of 2005, with just over 14 doctors, nurses and midwives per 10,000 population, and 34% of the recommended minimum number of EmONC facilities available in 2008 (UNICEF and WHO, 2015). This suggests that the health workers and infrastructure exist within the country, but policies and implementation could be strengthened.

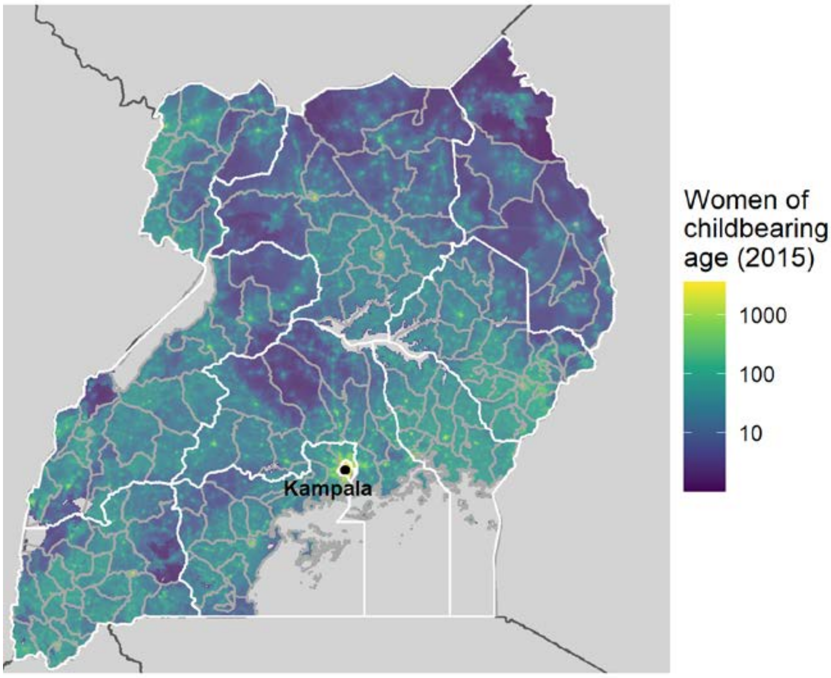


Figure 3.6. Distribution of women of childbearing age in Uganda, 2015. White lines delineate 2016 DHS boundaries, while grey lines delineate administrative II units.

3.5 Study methods

To estimate spatially and temporally disaggregated probabilities of utilisation of MNH services, statistical methods are needed which can estimate parameters of sub-populations at geographically small areas while accounting for sample error and study design (Ebener et al., 2015). Several approaches such as small area estimation (SAE), mixed effects modelling, and Bayesian inference exist to accomplish this, each with their own caveats. Within MNH research, SAE models provide a powerful tool for researchers to link measures of interest at small geographic areas (such as census enumeration areas) with covariates of interest to model estimates at these small areas (Ebener et al., 2015). Two broad SAE methodologies include area level techniques (Fay and Herriot, 1979), where covariates are available at the areal level, and nested-error models (Battese et al., 1988), where covariate information is available at the individual level and linked to primary measures at the areal level (Ebener et al., 2015). These methods have been used within MNH research to link demographic and fertility data from household surveys (such as the DHS) to census data, where prevalence of contraceptive use could be derived at geographic areas smaller than the DHS regions where estimates were reported (Johnson et al., 2012). The applications of these approaches can be limited, however, by methodological considerations and data limitations (Ebener et al., 2015), especially in scenarios with zero-inflated data (Chandra and Sud, 2012), or in situations where auxiliary data such as census data are difficult to obtain or proprietary.

In this work, I employed a hierarchical mixed effects modelling approach, followed by a structured additive regression model within a Bayesian framework. Notably, hierarchical mixed effects modelling and Bayesian models are able to produce geospatially interpolated estimates at geographical administrative units smaller than the boundaries at which the data were sampled (Gething et al., 2015), while also accounting explicitly for spatial correlation and utilising openly available data. These methods therefore make them ideal for inclusion in this work to address the research objectives outlined in Section 3.2.

Specifically, mixed effects modelling approaches have been utilised previously in the literature when working with DHS data, and are ideal for accounting for the multistage sampling design of the data (Magadi and Desta, 2011; Snijders and Bosker, 1999). I further expand the multilevel approach used in Chapter 4 to include a latent Gaussian regression model within a Bayesian framework in the third chapter. Specifically, I use the Integrated Nested Laplace Approximation (INLA) regression technique in Chapters 5 and 6 to control for spatially and temporally correlated effects using the DHS data. This technique has similarly been utilised with the DHS literature to predict small area outcomes, while also quantifying associated uncertainty (Achia, 2014; Gething et al., 2015; Mtambo et al., 2015; Neal et al., 2016; Niragire et al., 2015).

3.5.1 Hierarchical mixed effects modelling

In Chapter 4, I model the probability of receiving 4+ ANC visits before delivery, SBA during delivery, and receiving PNC within 48 hours of delivery, using DHS data throughout the Burundi, Kenya, Rwanda, Tanzania and Uganda. I visualise these probabilities firstly at a high-resolution (300 x 300 m grid cells), and then aggregate to more policy relevant scales (administrative level 2, typically districts) to highlight spatial heterogeneity and sub-national inequalities in MNH care utilisation throughout the region of interest. By producing estimates at a high spatial resolution such as 300m, these probabilities can be aggregated and visualised at any policy-relevant level later on, including administrative boundaries, health catchment boundaries, or census enumeration areas. These estimates therefore represent substantive methodological contributions (at the 300m scale) to the literature, as well as policy contributions (at the administrative level 2 boundary).

Because of the importance of physical accessibility for care utilisation, my primary explanatory variable of interest is geographic inaccessibility to the nearest health facility. Towards this, I explore MNH utilisation within this context by creating a gridded travel impedance surface reflecting overall ease of traversing each 300 x 300 m square in the study region, given the topography and transport infrastructure of the region. Because consolidation of the various input data sources (e.g., land cover, elevation, water bodies, etc.) necessitate identical cell size, data were aggregated to the coarsest resolution available, thereby driving a 300m resolution. I subsequently use this impedance surface to inform a cost-distance analysis, generating a geographic inaccessibility score for each 300 m grid cell. These scores range from 0 (highly accessible) to 7 (highly inaccessible) and represent ease of access to the nearest health facility among a dataset of 9,314 facilities. I include this inaccessibility score as a covariate in a hierarchical mixed effects logistic regression model by overlaying DHS cluster locations on this generated accessibility surface and extracting scores for each cluster location. Finally, I use the resulting model of best fit to visualise probabilities of obtaining MNH care for each 300 x 300 m square throughout the region. Random effects included in the model consist of DHS regions (N = 61) within five EAC countries, while fixed covariates include cluster-level (N = 3,311) effects of accessibility and rurality, and individual-level (N = 25,325) effects of wealth, education, and an interaction between age and total children delivered.

3.5.2 Bayesian modelling

In Chapters 5 and 6, I extend the hierarchical spatial methodologies outlined in Chapter 4 by incorporating temporal change and controlling for spatial effects using a Bayesian inference framework. Specifically, I extend the previous methodologies among ANC, SBA, and PNC indicators to include multiple time points using geo-located DHS surveys extending backwards in time as far as 1999. To create these surfaces, I utilise a structured latent Gaussian additive model, which has been used in the literature previously to control for spatially and temporally correlated effects which are common to DHS datasets (Achia, 2014; Gething et al., 2015; Mtambo et al., 2015; Neal et al., 2016; Niragire et al., 2015). I report both absolute and relative inequality measures, including visualization absolute difference in sub-national coverage estimates per administrative II unit, using the first and last time points available. I also report relative inequality measures by plotting ratios and regression coefficients of best versus worst performing administrative units for each time point available within the study countries, reflecting countries where progress has been made in lessening inequalities and countries with little to no change. Model results and associated posterior parameters such as inter-quartile range are reported, with aims of highlighting sub-national areas in the EAC region where spatial inequalities have narrowed, widened, or remained the same.

Finally, in Chapter 6, I again employ a Bayesian hierarchical modelling framework, utilising a stochastic partial differential equation (SPDE) spatial regression approach in order to predict outcomes at a continuous spatial resolution, implemented using the Integrated Nested Laplace Approximation (INLA) technique within the R-INLA package (Rue et al., 2009). This approach was suitable for these analyses as these spatial processes are generally well captured by a Gaussian field with Matérn correlation (Blangiardo and Cameletti, 2015). Similar models have been used in previous research combining DHS data and geospatial covariates to predict high-resolution childhood vaccination coverage by disaggregating aerial surveillance data (Bosco et al., 2017; C. Edson Utazi et al., 2018b; C. E. Utazi et al., 2018), and specifically allow for a statistical link between the areal DHS data and high-resolution spatial covariates and random effects (C. E. Utazi et al., 2018). I estimate prevalence of delivery via c-section at the 5km, 50km, and 100km scales in order to quantify the trade-off between model outcomes and associated uncertainty at increasing spatial resolution. I explore the posterior distribution of the 95% credible intervals at each spatial resolution, and visual outcomes and uncertainty at these spatial resolutions.

3.6 Scientific contribution

3.6.1 Knowledge gaps

With the close of the MDG agenda in 2015, Ebener and colleagues sought to outline the state of the field of maternal and newborn health geography, synthesizing what methods and techniques had been utilised in the field at the time (Ebener et al., 2015). They further established a comprehensive framework for analytic methods and outlining what work needed to be done moving into the future. Performing a “rapid” literature review, they identified 33 studies that were geographical in scope and analysing MNH outcomes, consolidating these studies into a table outlining the geographical scope, study aims and objectives, analytic methods and frameworks used, and region and country of study interest. Overall, they found a substantial increase in the number of studies employing spatial methods within the field of maternal and newborn health since 2010, most commonly studying geographic access to health services. Based on this literature review, they summarized three primary analytic objectives observed in the literatures: “1) thematic mapping (creation of maps to convey information about a topic or theme); 2) spatial analyses (extraction or creation of new information from spatial data); and, 3) spatial modelling (spatial analysis that includes the use of a mathematical model to simulate natural or anthropogenic phenomena)” (Ebener et al., 2015). Despite the encouraging trend towards increased use of GIS techniques and spatial methods within MNH, they note that little within-country capacity exists to continue supporting these analytic demands over the years, preventing crucial monitoring over time of disaggregated data and health inequalities.

This state of the art paper was soon followed up by a scoping literature review performed by Makanga and colleagues, evaluating the use of GIS techniques within the field of MNH and identifying knowledge gaps and opportunities from 70 studies (Makanga et al., 2016). Echoing findings from Ebener et al., they noted two key themes emerged surrounding modelling access to maternal services and identifying risks associated with adverse maternal outcomes. Specifically, they noted that the majority of articles modelling access to maternal services focused on “geographic access to care on the basis of the spatial distribution of [primary] health facilities”, with few articles examining access to tertiary level of care. Further, they noted that the majority of studies examining access to care neglected low- and middle-income countries, among which disproportionately bear a high burden of adverse maternal health outcomes. Lastly, they identified a key gap in knowledge needing prioritization over the coming years is incorporation of seasonal variation in spatial modelling of access to care, where many studies do not have any temporal effect (Makanga et al., 2016).

Finally, Gabrysch and Campbell performed a systematic literature review to identify determinants of accessing skilled birth attendance during delivery within low- and middle-income countries (Gabrysch and Campbell, 2009a). Among the overall themes emerging from this review was the effect of physical accessibility. Similarly discussing the effect of accessing care and distance, they also noted that the effect of distance of health facilities may be intensified when combined with lack of transportation options or poor road infrastructure. Further, they found the effect of distance is also impacted by the perception of quality, with women willing to travel further distances for health facilities offering higher perceived quality of services. Despite the role of distance and transport on service utilisation, they noted a lack of high quality, comparable geographical data limited further analysis of the role of physical accessibility on maternal health outcomes, suggesting many studies have failed to address this important need (Gabrysch and Campbell, 2009a).

3.6.2 Contribution to the literature

Knowledge gaps persist in identification of inequalities in health and access to health services using high quality, comparable disaggregated data. Identifying these disparities in high-resolution over both space and time will be critical in ensuring SDG targets are achieved by the year 2030 (Requejo and Bhutta, 2015; WHO, 2015a). Comparable spatial and temporal disaggregation of maternal child health is an important first step in identifying where and why disparities are occurring within countries, as well as monitoring their progress over time. Establishing scientifically rigorous methodologies for achieving the spatial and temporal disaggregation of health data will therefore prove applicable for not just the poorest countries in the world, but for all countries in which inequalities persist. Further, working closely with in-country partners who have a quantifiable stake in improving the health of their constituents, as well as an in-depth understanding of the social and cultural context in which these disparities occur, will be key to ensuring sustainable solutions are found that will have lasting impact well beyond the SDG era.

Here, this work makes novel substantive and methodological contributions to the body of maternal and newborn health epidemiology literature through spatial and temporal disaggregation of inequalities in MNH care at high-resolution and policy relevant scales across multiple countries in East Africa. While previous studies have modelled travel time or distance to facilities, fewer have examined utilisation of MNH services as an emergent property of geographic accessibility. Among those studies which have explored the impact of geographic accessibility on choice or utilisation of MNH services, analyses have predominantly been performed on the national scale (Gabrysch et al., 2011; Pilkington et al., 2012). Among those studies which have performed sub-national analysis, analyses have been predominantly limited to a single country (Målqvist et al., 2010). No prior studies have quantified high-resolution spatial inequalities in utilisation of MNH services among multiple countries within a geographic region, nor highlighted how these spatial inequalities have changed over time on a sub-national scale, in both absolute and relative terms.

This work aims to fill in these gaps when such analyses are particularly needed as the world progresses through the SDG era. To ensure sustainability and community engagement in line with SDG targets, results from Chapters 4 and 5 are contextualized with input and collaboration from relevant stakeholders, such as policy makers through the intergovernmental East African Community (EAC), allowing for both academic contribution and real-world impact. The outputs of this research therefore work synergistically to add to the academic body of literature, while informing policy efforts and promoting policy relevance through collaboration with intergovernmental partners in the study region to ensure no one is left behind moving into the SDG era.

However, the production of MNH estimates at high spatial resolutions has important methodological limitations which should be fully considered, lest results are over-interpreted (Boerma et al., 2018). Towards this, the analyses comprising Chapter 6 of this work make substantial contributions to the academic literature by exploring the theoretical trade-off between increasing spatial resolution in model inputs, and resulting model uncertainty in estimates. While the production of global estimates at high spatial resolutions has been on the rise, no studies have commented on the optimal spatial resolution at which to report outcomes, or specifically examined the effect of increasing spatial resolution on modelled estimates. By quantifying this trade-off, this work fills an important knowledge gap, and further presents a novel method by which to communicate associated uncertainty to policy makers in a more intuitive way.

3.6.3 Impact

These analyses were conceptualized and implemented with feedback and collaboration through policy makers at the East African Community, an intergovernmental organization representing a coalition of member states in Burundi, Kenya, Rwanda, South Sudan, Tanzania and Uganda. Before analyses began, CWR travelled to EAC Headquarters based in Arusha, Tanzania, to discuss policy needs and knowledge gaps with the Principal Health Systems and Policy Analysis Officer working with the EAC Secretariat within the Reproductive Maternal Newborn Child and Adolescent Health (RMNCAH) group. Throughout the period of analysis, I consulted officers at the EAC for guidance on ensuring analyses and results were within the scope of ongoing EAC activities and needs. Based on this collaboration, results from Chapter 4 have been used within regional policy briefs funded by the UNFPA’s East and Southern Africa Regional Office representing the state of SRMNAH workforce in the region. Lastly, to ensure these analyses have ongoing and sustainable impact, I travelled to EAC Headquarters to conduct a within-region GIS Workshop, with over 25 delegates representing all 5 member states (South Sudan was not a member state at the time of the workshop). Based on this workshop, future GIS needs and objectives were outlined by the EAC Secretariat, including increased GIS infrastructure, data, and analytic capacity.

Lastly, the analyses comprising Chapter 4 of this work were recently internally assessed for inclusion in the 2021 Research Excellence Framework assessment for the Department of Geography and Environmental Science at the University of Southampton, receiving 3 stars out of 4 in ‘quality that is world-leading in terms of originality, significance and rigour’. This work therefore directly contributed to the department’s standing in assessing the quality of research in UK higher education institutions, helping to increase the university’s prestige and ranking.

3.6.4 Intellectual contribution

CWR conceptualized the study framework and methods used throughout this thesis, and performed all analysis, preparations, and writing of the final thesis and associated manuscripts. CWR also generated all study visualizations and graphs throughout this work. AJT and ZM supervised CWR throughout study conceptualization and application, while other post-doctoral researchers and postgraduate students in the WorldPop research group provided feedback on methodological applications and procedures. Other co-authors and collaborators involved in publication of manuscripts comprising this work, along with their specific contributions, are listed individually within the ‘Intellectual Contribution’ section for each corresponding chapter.

Chapter 4: Equality in maternal and newborn health: Modelling geographic disparities in utilisation of care in five East African countries

4.1 Abstract

Geographic accessibility to health facilities represents a fundamental barrier to utilisation of maternal and newborn health (MNH) services, driving historically hidden spatial pockets of localized inequalities. Here, I examine utilisation of MNH care as an emergent property of accessibility, highlighting high-resolution spatial heterogeneity and sub-national inequalities in receiving care before, during, and after delivery throughout five East African countries. Specifically, I calculate a geographic inaccessibility score to the nearest health facility at 300 x 300 m using a dataset of 9,314 facilities throughout Burundi, Kenya, Rwanda, Tanzania and Uganda. Using DHS data, I utilise hierarchical mixed effects logistic regression to examine the odds of: 1) skilled birth attendance, 2) receiving 4+ antenatal care visits at time of delivery, and 3) receiving a postnatal health check-up within 48 hours of delivery. I apply model results onto the accessibility surface to visualise the probabilities of obtaining MNH care at both high-resolution and sub-national levels after adjusting for live births in 2015.

Across all outcomes, decreasing wealth and education levels were associated with lower odds of obtaining MNH care. Increasing geographic inaccessibility scores were associated with the strongest effect in lowering odds of obtaining care observed across outcomes, with the widest disparities observed among skilled birth attendance. Specifically, for each increase in the inaccessibility score to the nearest health facility, the odds of having skilled birth attendance at delivery was reduced by over 75% (0.24; CI: 0.19 – 0.3), while the odds of receiving antenatal care decreased by nearly 25% (0.74; CI: 0.61 – 0.89) and 40% for obtaining postnatal care (0.58; CI: 0.45 – 0.75). Overall, these results suggest decreasing accessibility to the nearest health facility significantly deterred utilisation of all maternal health care services. These results demonstrate how spatial approaches can inform policy efforts and promote evidence-based decision-making, and are particularly pertinent as the world shifts into the Sustainable Goals Development era, where sub-national applications will become increasingly useful in identifying and reducing persistent inequalities.

4.2 Introduction

Worldwide maternal deaths have been cut nearly in half over the past two and a half decades, largely due to a committed global effort to improve the lives and wellbeing of the world's most vulnerable populations (Alkema et al., 2016a). Despite substantial progress among even the most disadvantaged subgroups, pregnancy remains risky for many of the world's women, and inequalities persist across the socioeconomic spectrum (WHO, 2015a). These risks are borne unequally both between and within countries, with pockets of relatively remote women in rural and poor communities bearing a disproportionate burden of morbidity and mortality (Alkema et al., 2016a). Historically, however, MNH policy has largely relied on aggregate, national-level statistics, which often mask these underlying spatial pockets of sub-national inequalities (Bhutta ZA and Reddy K, 2012). The United Nations therefore announced new SDGs to reduce these disparities and promote health and well-being for all, with specific targets to improve maternal and newborn health (MNH) outcomes among all women and children alike, and a particular emphasis on sub-national monitoring (United Nations General Assembly, 2015). As achieving these SDG targets will necessarily require effective use of limited resources, academics and policymakers alike have begun encouraging spatial disaggregation of health data (Countdown Core Group, 2014). Advances in computational geostatistical techniques and the increasing availability of geo-located data have increased the ability to produce these fine spatial resolution maps, critical for uncovering historically overlooked disparities. By monitoring health within a spatial framework, policy makers can better focus resources and intervention efforts amongst the most disadvantaged and marginalized populations, ensuring advancement of SDG targets in reducing inequalities among all (ICSU, ISSC, 2015).

Ultimately, achieving these targets and accelerating progress towards reducing adverse MNH outcomes requires understanding use of pregnancy-related services before, during, and after delivery, in addition to understanding the underlying disparities that drive observed utilisation patterns (Kerber et al., 2007). Specifically, the WHO has identified several critical determinants in reducing preventable pregnancy-related morbidity and mortality as: 1) access to antenatal care during pregnancy, 2) skilled birth attendance during delivery, and 3) postnatal care in the days and weeks following birth (World Health Organization, 2016b). Care seeking behaviour throughout the duration of a woman's pregnancy, however, is a complicated decision fraught with delays and barriers, including individual beliefs, societal norms, monetary barriers, and geographic access to necessary services (De Allegri et al., 2011).

Several studies have identified geographic accessibility specifically as a fundamental barrier in obtaining MNH care among developing nations, driving persistently high maternal and neonatal mortality rates (Ebener et al., 2015; Gething et al., 2012). This physical accessibility is driven by various geographic factors such as distance to the nearest health facility, topography of the local landscape, household transportation capacity, and road network infrastructure, all synergistically determining the extent and duration to which a woman can seek and obtain care (Jones-Webb and King-Schultz, 2008; Målqvist et al., 2010). Studies have therefore called for a nuanced understanding of accessibility as central to assessing maternal and newborn health and guiding policy interventions (De Allegri et al., 2011; Ebener et al., 2015; Gething et al., 2012; United Nations, 2013).

The use of spatial statistics has become an increasingly recognised methodology to identify these hidden gaps, as geographic and spatial dynamics largely drive physical accessibility. These techniques can be used to extend an understanding of accessibility to produce policy relevant, high-resolution maps that can be used to focus resources where pregnancy is often riskiest (Ebener et al., 2015). Despite this, current spatial analyses of maternal and newborn health remain limited, and spatially explicit data currently available (such as geo-referenced DHS and Service Provision Assessment (SPA) surveys) remain underutilised (Gabrysch and Campbell, 2009a; Larmarange et al., 2011). While previous studies have examined the impact of geographic accessibility on a handful of MNH outcomes, few studies have explored accessibility as a determinant across the spectrum of pregnancy, particularly at a disaggregated level.

Here, I examined several MNH outcomes in the context of geographic accessibility to map the likelihood of receiving care before, during, and after delivery. Specifically, I utilised a geo-referenced dataset of nearly 10,000 health facilities to generate high-resolution surfaces and administratively relevant maps reflecting the probability of a woman obtaining critical MNH care throughout the five East African Community partner states. By mapping disaggregated MNH outcomes as a function of geographic accessibility, outputs of these analyses have important policy implications in focusing future intervention efforts and allocation of resources, as well as providing a baseline from which to monitor future progress in the SDG era.

4.3 Methods

4.3.1 Overview

In this study, I modelled the probability of a woman receiving 4+ antenatal care (ANC) visits before delivery, skilled birth attendance (SBA) during delivery, and receiving postnatal care (PNC) within 48 hours of delivery, using DHS data throughout Burundi, Kenya, Rwanda, Tanzania and Uganda. I visualised these probabilities at both high-resolution (300 x 300 m grid cells) and policy relevant (administrative level 2, typically districts) scales to highlight spatial heterogeneity and sub-national inequalities in MNH care utilisation throughout the region of interest. Because of the importance of physical accessibility for care utilisation, my primary explanatory variable of interest was geographic inaccessibility to the nearest health facility.

To explore MNH utilisation in the context of geographic inaccessibility, I created a gridded travel impedance surface reflecting overall ease of traversing each 300 x 300 m square in the study region, given the topography and transport infrastructure of the region. I subsequently used this impedance surface to inform a cost-distance analysis, generating a geographic inaccessibility score for each 300 m grid cell. These scores ranged from 0 (highly accessible) to 7 (highly inaccessible) and represented ease of access to the nearest health facility among a dataset of 9,314 facilities. I included this inaccessibility score as a covariate in a hierarchical mixed effects logistic regression model by overlaying DHS cluster locations on this generated accessibility surface and extracting scores for each cluster location. Finally, I used the resulting model of best fit to visualise probabilities of obtaining MNH care for each 300 x 300 m square throughout the region. Random effects included in the model consisted of DHS regions (N = 61) within the five countries, while fixed covariates included cluster-level (N = 3,311) effects of accessibility and rurality, and individual-level (N = 25,325) effects of wealth, education, and an interaction between age and total children delivered.

4.3.2 Data

4.3.2.1 Assembling individual-level MNH data

To explore variations in utilisation of MNH care across central East Africa, I obtained data from the most recent standard DHS for each country: Kenya (2014), Tanzania (2010), Uganda (2011), Rwanda (2010), and Burundi (2010) (Institut de Statistiques et d'Études Économiques du Burundi (ISTEEBU), Ministère de la Santé Publique et de la Lutte contre le Sida Burundi (MSPLS), and ICF International Inc, 2012; Kenya National Bureau of Statistics (KNBS) and ICF Macro, 2010; National Bureau of Statistics (NBS) Tanzania and ICF Macro, 2011; National Institute of Statistics of Rwanda (NISR), Ministry of Health (MOH) Rwanda, and ICF International Inc, 2012; Uganda Bureau of Statistics (UBOS) and ICF International Inc, 2012). Data were combined and processed using SAS v. 9.4 software, (SAS Institute Inc., 2013) with a total of 72,952 respondents between the five countries. For these analyses, I included women with a birth in the preceding five years, resulting in a total of 36,460 women. I obtained corresponding GPS coordinates for cluster locations via the DHS (for detailed methods, see http://dhsprogram.com/What-We-Do/GPS-Data-Collection.cfm) and mapped these using ArcGIS 10.2.2 software (Environmental Systems Research Institute, 2014).

To maintain participant confidentiality, the DHS randomly displaces GPS locations, with displacement diameters varying by urban (up to 2 km) and rural (up to 5 km, with 1% up to 10km) location (Burgert et al., 2013). To minimize displacement bias, I therefore drew corresponding buffers (circles placed around point locations with a specified diameter) of 2 km and 5 km around cluster locations to be used in later analyses, according to DHS guidelines (Perez-Heydrich et al., 2015). Only women with associated cluster locations were consequently included in further analyses, with 36,178 women among 3,311 clusters (see Figure A.1). Finally, to allow for subsequent model validation, I trained the model using 70% of the total sample with the remaining 30% set aside for model validation, resulting in 25,325 women used in the final model (see Appendix A for model validation details).

The University of Southampton Ethics and Research Governance approved secondary analysis of these data (ethics approval number 16918). Survey data used in these analyses are freely available via the DHS website, and participant confidentiality is outlined further at http://dhsprogram.com/What-We-Do/Protecting-the-Privacy-of-DHS-Survey-Respondents.cfm.

4.3.2.2 Assembling a database of health facilities

With input and collaboration from the intergovernmental East African Community (EAC) Secretariat, I obtained health facility data from ministries of health on over 19,000 mapped facility locations throughout the five EAC partner countries. These data included information for each health facility on operational status, private/public ownership, and type, and initially included dispensaries, maternity homes, district hospitals, health centres, and health posts. In the presented analyses, I included national, district, or regional hospitals, maternity homes, and health centres, and excluded dispensary facilities, as these facilities do not reliably offer comprehensive MNH care, including inpatient care critical for skilled birth attendance and postnatal care (Muga et al., 2005). After excluding dispensary facilities and cleaning the dataset to correct for duplicate entries or incorrect coordinates, I used a remaining 9,314 facilities in my cost-distance analyses. Finally, I imported this final list of health facilities into ArcGIS software and geo-located facility locations using latitude and longitude coordinates within the dataset to create a shapefile of health facility locations throughout the study countries (see Figure 4.1b).

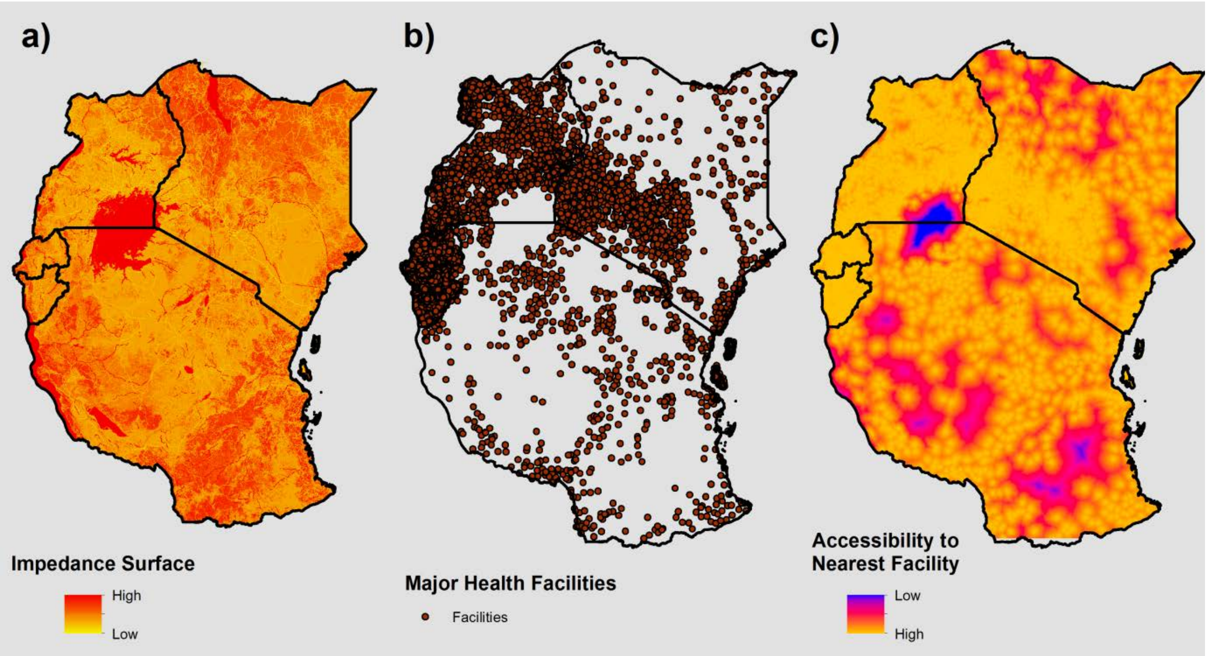


Figure 4.1 Mapping inaccessibility to the nearest health facility. A) Impedance surface representing the difficulty in traversing a given 300 x 300 m cell. B) Health facility locations used as destinations. C) Accessibility surface generated via cost-distance analysis using inputs A) and B), representing the least accumulative geographic “cost” value for a 300 x 300 m cell in accessing the nearest health facility.

4.3.3 Creating an impedance surface and inaccessibility score

I combined these health facilities with a gridded impedance surface representing difficulty of travel through a given cell to generate a geographic accessibility surface that reflected the most efficient, or least "cost" accumulative, pathway to the nearest health facility. I created this impedance surface for the study region by combining data on primary, secondary and tertiary road networks, permanent water bodies and river networks via DIVA-GIS (freely available at www.diva-gis.org), land cover data from the European Space Agency's 2009 GlobCover initiative, and elevation data from the Advanced Spaceborn Thermal Emission and Reflection Radiometer-Global Digital Elevation Model (ASTER-GDEM) Version 2 (*ASTER Global Digital Elevation Model Version 2*, 2011; *Global Land Cover Map (GlobCover)*, 2009). These surfaces were rasterized, or gridded, and consolidated to create a single surface where travel speeds could be assigned to each cell. Because consolidation of these surfaces necessitates identical cell size, I aggregated data to the resolution of the coarsest surface, thereby driving a 300 x 300 m resolution throughout further analysis.

To assign travel speeds to each 300 m cell, I built upon methods outlined previously by Alegana et al. 2012 (Alegana et al., 2012). While previous studies have modelled likely mode of transport used to access health facilities using sparse survey data and small area estimation approaches, (Gething et al., 2012) similar data were not available for all study countries used in these analyses. I therefore assumed mechanised transport on primary and secondary road networks, walking for off-road and tertiary networks, and that major water bodies were not traversable. For primary and secondary road networks, I assigned driving speeds of 80 and 60 km/hour, respectively. While maximum travel speeds for all five countries vary considerably, these speeds have been used in the literature previously, and were conservative estimates among the five countries (Alegana et al., 2012; Bureau for Industrial Cooperation, 2011). For cells not containing road networks, I classified land cover into broad categories such as tree, shrub or herbaceous cover, water body, and cultivated/managed or bare area. I then assigned these categories associated walking speeds, ranging from 2 km/hour (for desert area) to 5 km/hour (for cultivated or built areas). I inferred slope from elevation data using the Slope tool in ArcGIS software, and incorporated this into walking speeds based on Tobler's equation, which adjusts for increased walking speed on down-slopes and decreased walking speed on up-slopes (Tobler, 1993). Permanent major rivers and other large water bodies represented a barrier to movement in these analyses, and were therefore designated a walking speed of 0 km/hour. For a detailed list of land cover classification and associated travel speeds, see Alegana *et al.* 2012 (Alegana et al., 2012). Finally, these discrete travel speed definitions were used to create standardized, ranked 'impedance' indices across the study region ranging from 1 to 7, where 1 represented the fastest travel speed (80 km/hr) and 7 represented the slowest speed (0 km/hr). The resulting impedance surface was then used in the cost-distance analyses (see Figure 4.1a).

Using this impedance surface, I created an overall inaccessibility score by performing a least accumulative cost-distance analysis using the Cost Distance tool in ArcGIS software. Briefly, this tool calculates the total geographic "cost"—a relative estimate of accessibility to a “source”, in this case health facilities—for each 300 m square throughout the study region, given an input impedance (or “cost”) surface. For each cell within the gridded raster, the pathway representing the least “cost” between a defined origin and defined destination is calculated; in general, “cost” may represent distance, geography, economic cost, or anything else the user defines. In my analyses, however, “cost” is defined by the created impedance surface, representing landscape, the built environment, and road infrastructure. The analyses performed here are similar, therefore, to Euclidean distance analyses (which simply measure shortest distance from origin to destination), with the added benefit of calculating the shortest *weighted* distance, incorporating factors such as bodies of water, landscape type, and use of road networks. This therefore measures not only distance, but also *accessibility*, between an origin (each 300m cell within the study area) and destination (health facility). Here, each square's calculated inaccessibility score, ranging from 0 (highly accessible) to 7 (highly inaccessible), represents the sum of the impedance values of traversed cells when traveling from that square to the facility with the lowest overall travel “cost”. Therefore, higher scores on this index represent greater geographic “cost” and greater difficulty in reaching the nearest health facility.

Figure 4.1 outlines the inputs and output of this analysis, representing a) the impedance surface as described above (i.e., origin), b) facility locations (i.e., destination), and c) the resulting accessibility surface from the cost distance analysis. Using this accessibility surface, I subsequently overlaid buffered DHS cluster locations (as outlined in Section 3.3.2.1), and extracted the mean score throughout the buffers to include as an explanatory variable in exploring probabilities of obtaining MNH care. I chose to extract the mean score because DHS clusters can be located anywhere within the displacement radius, and therefore choosing one value (be it the minimum or maximum value within the buffer) is probabilistically not likely to reflect the actual underlying value of the true cluster location, thereby biasing results. To quantify this phenomenon common to geographical studies, Perez-Heydrich and colleagues performed a sensitivity study examining the ancillary raster extraction on DHS cluster locations, finding that simple point extraction does not bias results for continuous rasters, analyses extracting data from categorical raster surfaces are recommended to use buffer means (Perez-Heydrich et al., 2015). I therefore employed buffer means to mitigate this potential displacement bias, as the accessibility surface was a categorical raster ranging from 0 to 7. Lastly, because the impedance surface incorporates information on travel speed, the resulting accessibility surface units may be translated to travel time to the most accessible health facility. However, as the accessibility surface was used as an input covariate into the hierarchical model, this further translation was redundant and beyond the scope of this study.

4.3.4 Analysis of MNH outcomes

4.3.4.1 Hierarchical mixed effects modelling of MNH indicators

I used the inaccessibility score associated with DHS cluster locations to model the MNH outcomes of interest in the DHS data. The primary outcomes examined in these analyses included skilled birth attendance, antenatal care, and postnatal care, chosen through feedback from policy makers at the EAC organisation based on their programmatic relevance and impact. I modelled these outcomes using hierarchical mixed effects logistic regression using the 'lme4' package in R software (Bates et al., 2014, p. 4). Such multilevel analyses have been used previously in the literature with DHS data to account for the inherent nesting structure and multistage sampling design of the data (Magadi and Desta, 2011; Snijders and Bosker, 1999). I employed a random intercepts model for each outcome, allowing the intercept to vary among DHS regions (n = 61) throughout the study area:

$$y_{ij} = \beta_0 + \beta_1 x_{ij} + \beta_2 x_{ij} \ldots + \beta_k x_{ij} + u_j + e_{ij}$$

where *y* is the dependent variable of interest, β_1 through β_k represent the array of independent variables of interest, *x* is the random effect of interest (in this case, DHS region), *u* is the group level effect, and *e* is the individual level error. In these models, I assumed u_j and e_{ij} are normally distributed with means 0 and variances σ_u^2 and σ_e^2.

Figure 4.2 outlines the hierarchical levels existing in these analyses: the individual level, the cluster level, and the regional level. By using hierarchical, mixed effects-based model inference, spatial variation as a result of region-specific contextual factors (such as road infrastructure and health financing) can be captured in the model which otherwise would have been unaccounted for, and the inherent nested sampling structure employed through the DHS may be controlled for, regardless of significance of the random effect itself (Barr et al., 2013; Snijders and Bosker, 1999).

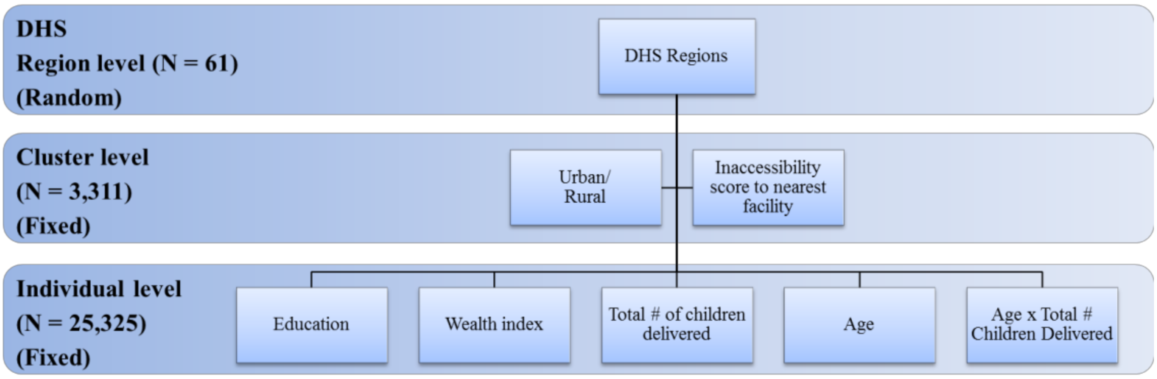


Figure 4.2 Hierarchical covariates included in the mixed-effects logistic regression analysis. Covariates are listed in boxes with corresponding hierarchy and fixed versus random effect.

In these analyses, I defined skilled birth attendance as assistance during delivery by any doctor, nurse, or midwife (as defined by country-specific DHS observations), while antenatal care was defined based on WHO guidelines as 4+ antenatal visits during pregnancy, and postnatal care was defined as the respondent's first check-up occurring within 48 hours of delivery. For ANC and PNC, the DHS captures information on the most recent live birth, while SBA is recorded among all births in the preceding 5 years. Therefore, ANC and PNC represent care received for the most recent live birth a woman had, while SBA represents the proportion of all births a women had in the preceding 5 years which had a skilled attendant present. By examining SBA among all births in the preceding 5 years, I included all available data for the 37,309 total births occurring among the 25,325 women used in these analyses. Figure 4.2 outlines specific covariates used in the models, with individual level fixed effect covariates including DHS wealth quintile, highest level of education obtained, and an interaction between number of children delivered and respondent age. Lastly, DHS regions (N=61) within the five countries were included in the model as a random effect to account for unexplained spatial variation and region-specific differences.

4.3.4.2 High-resolution mapping of MNH care utilisation

I applied the results of the best fit model across the previously described accessibility surface to visualise the probability of a given birth receiving MNH care for each 300 x 300 m grid square. However, underlying population distributions and human settlements are highly heterogeneous and therefore variable in birth rates, limiting direct applicability of these probabilities. Therefore, to present a more accurate reflection of actual births at risk of not receiving these critical MNH services, I sought to incorporate information on the current number of live births occurring sub-nationally for the year 2015, reflecting probability of a given birth obtaining MNH care in a more policy-relevant framework.

4.3.4.3 Estimating births-adjusted MNH care utilisation sub-nationally

The distribution of live births in the study region was obtained via the WorldPop project at a 100 m spatial resolution, freely available at www.worldpop.org (see Figure A.2) (UNFPA et al., 2014). Briefly, these data incorporate population demographics and satellite imagery data such as settlements, land cover, night-time lights, and sub-national age structure to model the distribution of women of childbearing age. Sub-national age-specific fertility rates, UN population projections, and estimates of abortions, stillbirths, and miscarriages are then used to model live births and pregnancies. Detailed methodology is outlined further in Tatem et al. 2014 (Tatem et al., 2014).

Using ArcGIS software, I adjusted the birth surfaces from 100 m to 300 m spatial resolution to match the resolution of the probability surface, multiplied the births and probability surfaces, and summed these values to the administrative unit level 2 to reflect actual number of births at-risk for each outcome. I then calculated the births-adjusted probability for each administrative level 2 unit throughout the region by dividing these at-risk births with total births in the administrative unit, as obtained from WorldPop. By incorporating data on live births, I present maps reflecting actual fertility rates, accounting for age structure, urban/rural differences, stillbirths, miscarriages, etc.

4.4 Results

Figure 4.3 represents the distribution of skilled birth attendance, no antenatal care visits, and postnatal care within 48 hours of delivery for the study area by DHS region, for three years preceding the survey. These thematic maps represent weighted estimates by DHS region, as compiled through the DHS's STATcompiler feature, with specific estimates outlined in Table 4.1 (ICF International, 2015). DHS regions varied by indicator, with skilled birth attendance and postnatal care ranging from just under 25% skilled attendance at delivery in Pemba North, Tanzania to over 90% in Bujumbura Mairie, Burundi, and under 10% of women receiving a postnatal care check-up within 48 hours of delivery in Mwanza, Tanzania to over 70% in the Central DHS region in Kenya. Those receiving no antenatal care visits at all were far less than the previous two outcomes, with many DHS regions reporting 0% of women with no ANC visits, to a high of nearly 25% of women receiving no ANC visits in the North Eastern region of Kenya. In general, the North Eastern region of Kenya represented a consistently 'at-risk' region, with 23.8% of women having no antenatal visits, 35.3% of women having skilled birth attendance at delivery, and only 14.9% of women receiving a postnatal care check-up within 48 hours of delivery (Figure 4.3).

Table 4.1 MNH outcomes within the study area disaggregated by sub-national DHS region and national total, gathered through STATcompiler (ICF International, 2015)

DHS Year	DHS Region	No ANC	SBA	PNC
Burundi				
2010	Bujumbura Mairie	1.7	92.9	44.4
	North	0.5	60.3	28.3
	Centre-East	0.9	60.4	25.0
	West	1.2	70.6	35.1
	South	0.9	66.2	29.5
	TOTAL	**0.9**	**65.0**	**29.8**
Kenya				
2014	Central	1.9	90.2	71.9
	Coast	2.2	61.1	49.5
	Eastern	2.8	66	61.1
	Nairobi	1.6	91.1	71.6
	North Eastern	23.8	35.3	14.9
	Nyanza	2.2	68.3	61.0
	Rift Valley	6.4	53.5	45.9
	Western	2.1	54.6	34.6
	TOTAL	**4.0**	**64.5**	**52.9**
Rwanda				
2010	Kigali	1.1	86.0	24.8
	South	2.0	75.9	23.8
	West	1.5	77.4	13.2
	North	1.3	73.1	17.9
	East	1.9	77.1	13.6
	TOTAL	**1.7**	**77.1**	**17.6**
Tanzania				
2010	Dodoma	2.8	46.4	29.9
	Arusha	3.2	46.1	25.5
	Kilimanjaro	0.0	87.9	43.7
	Tanga	1.1	42	25.9
	Morogoro	0.9	58.3	20.2
	Pwani	0.0	74.7	35.8
	Dar es Salaam	0.0	88.1	43.0
2010	Lindi	0.0	55.2	31.8
	Mtwara	0.0	64.6	32.7
	Ruvuma	0.7	77.1	56.7
	Iringa	3.8	77.6	54.3
	Mbeya	4.9	42.1	25.6
	Singida	1.6	47.8	29.3
	Tabora	5.9	46.3	28.6
	Rukwa	2.0	29.5	13.6
	Kigoma	0.0	32.5	14.8
	Shinyanga	3.4	36.6	22.3
	Kagera	0.0	56	18.4
	Mwanza	0.5	40.6	8.6
	Mara	1.8	30.9	12.6
	Manyara	4.5	42.3	25.8
	Zanzibar North	0.2	43.6	13.6
	Zanzibar South	0.0	68.4	43
	Town West	0.0	77.0	41.7
	Pemba North	0.6	24.3	12.6
	Pemba South	1.1	42.0	25.2
	TOTAL	**1.9**	**49.9**	**25.8**
Uganda				
2011	Kampala	1.9	92.2	61.2
	Central 1	10.8	60.6	39.4
	Central 2	3.6	70.5	39.3
	East Central	8.1	67.7	24.5
	Eastern	5.3	58.1	31.2
	North	1.1	57.4	27.8
	Karamoja	2.0	31.1	26.8
	West Nile	2.0	62.0	40.5
	Western	2.5	52.6	24.1
	South West	0.8	46.8	18.8
	TOTAL	**4.1**	**59.5**	**33.0**

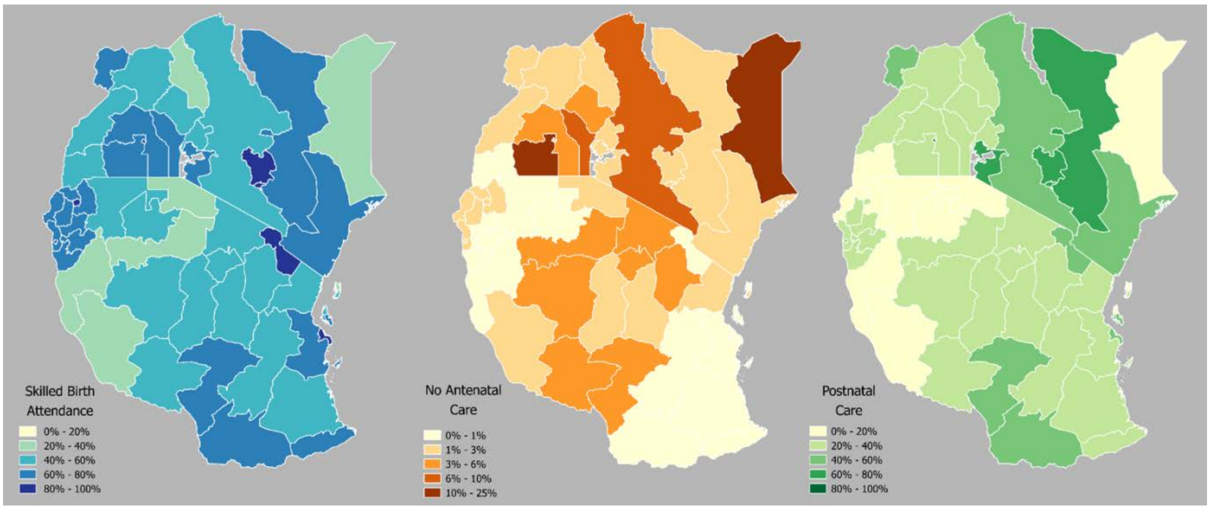


Figure 4.3 Prevalence of skilled attendance at delivery, no antenatal care, and postnatal care provided within 48 hours of delivery, by DHS region

4.4.1 Gridded accessibility surface

Figure 4.1c presents results of the cost-distance analysis, and represents geographic accessibility to the nearest health facility for a given 300 x 300 m square. Unsurprisingly, health facility distribution predominantly drives patterns in the accessibility surface, with remote areas lacking facilities representing the most inaccessible throughout the region, regardless of landscape topography. This result visually highlights the spatial patterns in accessibility emerging from the heterogeneous placement of major health facilities. Of note, the area of lowest accessibility observed in northern Tanzania and southern Uganda is a result of Lake Victoria, represented by red in Figure 4.1a. However, because neither health facilities nor DHS data are located in this area, results remain unaffected by this artefact.

4.4.2 Explanatory variables of MNH care utilisation

Table 4.2 presents modelled odds ratios and 95% confidence intervals for each MNH outcome. Across all outcomes, increasing wealth and education was associated with greater odds of obtaining MNH care, with the most disparities between groups observed among skilled birth attendance. Specifically, those in the highest wealth quintile had over 4 times odds of delivering with a SBA as compared to those in the lowest wealth quintile (4.71; CI: 4.22 – 5.25), while those with higher education had over 7 times the odds of having a SBA present at delivery (7.63; CI: 5.91 – 9.84). In contrast, those in the richest quintile had only a 1.5 to 2 times increased odds of obtaining ANC (1.52; CI: 1.36 – 1.70) and PNC (1.89; CI: 1.67 – 2.14) as compared to those in the poorest quintile, while those with the highest education had a 2 to 3 times increased odds of obtaining ANC (2.82; CI: 2.35 – 3.39) and PNC (1.92; CI: 1.61 – 2.28) as compared to those with no education.

Table 4.2 Hierarchical mixed effects logistic regression model odds ratios of MNH outcomes among female DHS respondents in five East African countries (N = 25,325)

Fixed Effects	**SBA**	**ANC**	**PNC**
	OR (95% CI)		
Age			
15 to 20	Ref	Ref	Ref
20 to 30	0.86 (0.69, 1.08)	1.28 (1.01, 1.61)	1.09 (0.84, 1.43)
30 to 40	0.54 (0.42, 0.69)	1.38 (1.07, 1.77)	1.15 (0.86, 1.53)
40 to 50	0.43 (0.29, 0.62)	1.09 (0.74, 1.6)	0.91 (0.59, 1.41)
Total # children delivered	0.64 (0.57, 0.72)	0.85 (0.73, 1)	0.87 (0.73, 1.04)
Wealth quintile			
Poorest	Ref	Ref	Ref
Poorer	1.41 (1.32, 1.51)	1.10 (1.02, 1.20)	1.28 (1.15, 1.41)
Middle	1.78 (1.65, 1.92)	1.18 (1.08, 1.29)	1.43 (1.29, 1.59)
Richer	2.50 (2.31, 2.71)	1.36 (1.24, 1.49)	1.69 (1.52, 1.88)
Richest	4.71 (4.22, 5.25)	1.52 (1.36, 1.70)	1.89 (1.67, 2.14)
Education			
No education	Ref	Ref	Ref
Primary	1.61 (1.51, 1.72)	1.04 (0.96, 1.12)	1.33 (1.21, 1.45)
Secondary	3.04 (2.75, 3.37)	1.29 (1.16, 1.43)	1.63 (1.44, 1.84)
Higher	7.63 (5.91, 9.84)	2.82 (2.35, 3.39)	1.92 (1.61, 2.28)
Residence			
Urban	Ref	Ref	Ref
Rural	0.69 (0.64, 0.75)	1.00 (0.92, 1.08)	0.90 (0.82, 0.98)
Accessibility to nearest facility	0.24 (0.19, 0.30)	0.74 (0.61, 0.89)	0.58 (0.45, 0.75)
Age x Total # Children Delivered			
15 to 20	Ref	Ref	Ref
20 to 30	1.19 (1.05, 1.34)	1.05 (0.90, 1.22)	1.01 (0.84, 1.21)
30 to 40	1.39 (1.23, 1.57)	1.08 (0.93, 1.26)	1.06 (0.88, 1.27)
40 to 50	1.44 (1.27, 1.64)	1.15 (0.98, 1.35)	1.10 (0.92, 1.33)
Random Effects	**SBA**	**ANC**	**PNC**
	Variance (SD)		
DHS Region	0.1923 (0.4385)	0.1422 (0.3770)	0.2248 (0.4741)

Living in rural areas was also associated with decreased odds of obtaining MNH care across outcomes. Specifically, those living in rural areas were 30% less likely to deliver with a skilled birth attendant present (0.69; CI: 0.64 – 0.75) and 10% less likely to obtain PNC after delivery (0.90; CI: 0.82 – 0.98) as compared to those living in urban areas. However, while living in rural areas was also associated with decreased odds of receiving 4+ ANC visits, this was not significant (1.00; CI: 0.92 – 1.08). Lastly, I found age and total number of children delivered were highly correlated, in line with previous studies (Magadi et al., 2007). Because both age and parity are important indicators in determining service use with sometimes opposing directionality, I included an interaction term in the model to control for the relationship between number of children delivered and respondent's age. This interaction term improved model fit and was highly significant in explaining skilled birth attendance ($p<0.0001$), with older women experiencing a greater increase in odds of SBA per child delivered as compared to younger women, and is in line with previous findings (Gabrysch and Campbell, 2009a). While similar patterns were observed among ANC and PNC outcomes, these effects were not significant.

Finally, increasing geographic inaccessibility to the nearest health facility was associated with the greatest reduction in odds of utilising MNH care, particularly among skilled birth attendance. Specifically, for each unit increase in inaccessibility to the nearest health facility, the odds of having a skilled birth attendant present at delivery was reduced by over 75% (0.24; CI: 0.19 – 0.30), while odds of receiving 4+ ANC visits decreased by nearly 25% (0.74; CI: 0.61 – 0.89) and 40% for obtaining PNC (0.58; CI: 0.45 – 0.75). Due to how I calculated inaccessibility scores (as outlined in Methods), these scores do not represent a directly interpretable index of travel time/difficulty, but quantify distance in grid cells to the nearest health facility, scaled by the relative speed of traversing each grid cell type. Overall, these results suggest decreasing accessibility to the nearest health facility significantly deterred utilisation of all maternal health care services.

4.4.3 High-resolution mapping of MNH care utilisation

I applied coefficients from the resulting model of best fit to the previously described accessibility surface to generate high-resolution maps reflecting probability of obtaining MNH care as an emergent effect of accessibility. Figure 4.4 presents boxplots for these distributions, while Figure 4.5 presents high-resolution probability surfaces among all MNH outcomes. The probability of having a skilled birth attendant during delivery exhibited the greatest amount of variability across the study region (Figure 4.4), with an average probability of 58%, ranging between nearly 0% and 75% for a given 300 x 300 m square. The ranges of receiving ANC and PNC were lower than SBA, with a mean probability of 37% (ranging from 9% to 40%) and 18% (ranging from <1% to 22%), respectively.

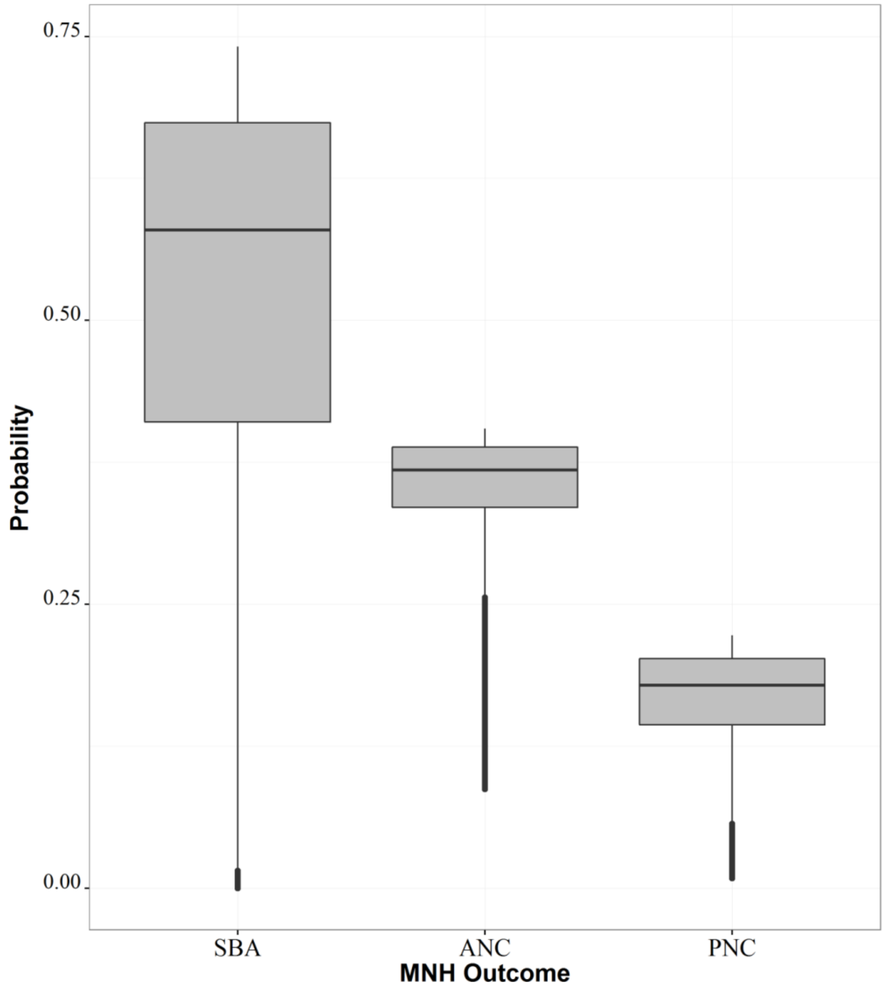


Figure 4.4 Boxplots of modelled probabilities of skilled birth attendance (SBA), antenatal care (ANC), and postnatal care (PNC).

Figure 4.5 shows the probability of MNH outcomes at 300 x 300 m, representing spatial heterogeneity in rates of obtaining care as a function of accessibility. As previously discussed, the ranges of probabilities varied widely between outcomes, making direct comparison between probability surfaces difficult due to the varying scales used between subfigures. Instead, this figure shows variations in the emergent spatial patterns resulting from geographic accessibility between outcomes, with the most drastic effect of space observed among SBA, as represented by more contained pockets of higher SBA probability surrounding health facility locations. This spatial effect becomes coarser for ANC and PNC utilisation, with relatively similar patterns observed between the two, despite varying probability distributions (Figure 4.5).

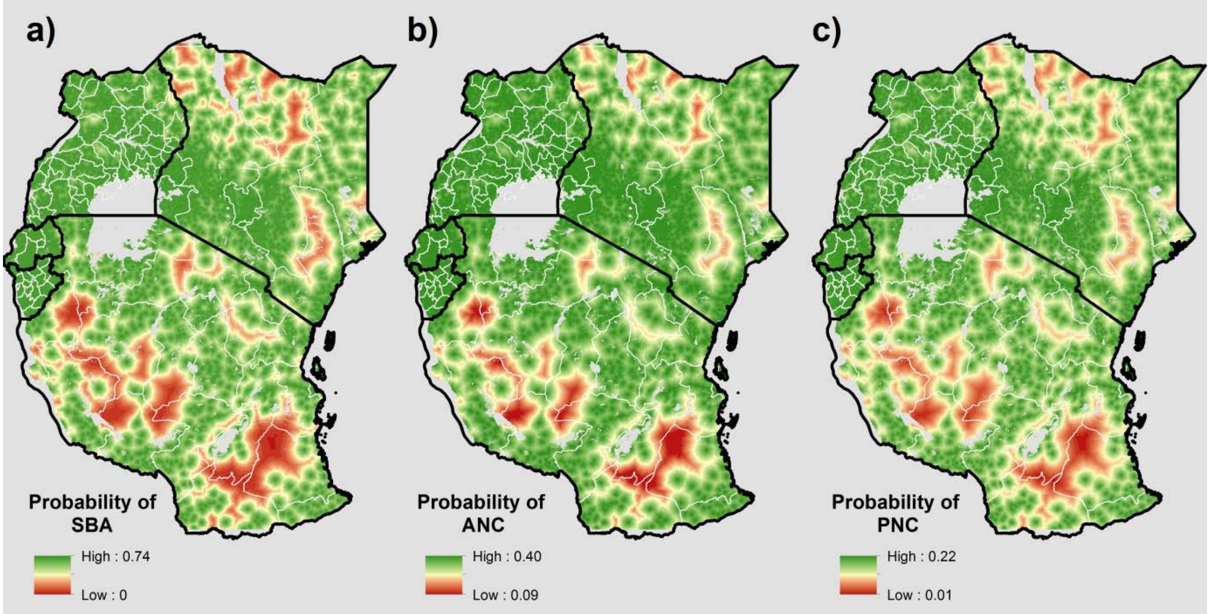


Figure 4.5 Modelled probability surfaces representing the spatial effect of accessibility at 300 x 300 m. a) Delivery with a skilled birth attendant (SBA) present, b) Four or more antenatal care (ANC) visits at time of delivery, and c) Postnatal care (PNC) received within 48 hours of delivery.

4.4.4 Sub-national mapping of MNH care utilisation

To facilitate policy relevance, I aggregated high-resolution probability surfaces to an administratively relevant scale, and adjusted these values using the surface of births per 300 m grid square, as previously described above. Figure 4.6 therefore represents the probability of: a) having a skilled attendant present during delivery, b) obtaining 4+ ANC visits by time of delivery, and c) the woman receiving PNC within 48 hours of delivery, respectively. Because I adjusted probabilities to reflect actual births at-risk, these maps represent the mean probability of obtaining MNH for a given birth within each geographic unit, accounting for where live births are most likely to occur.

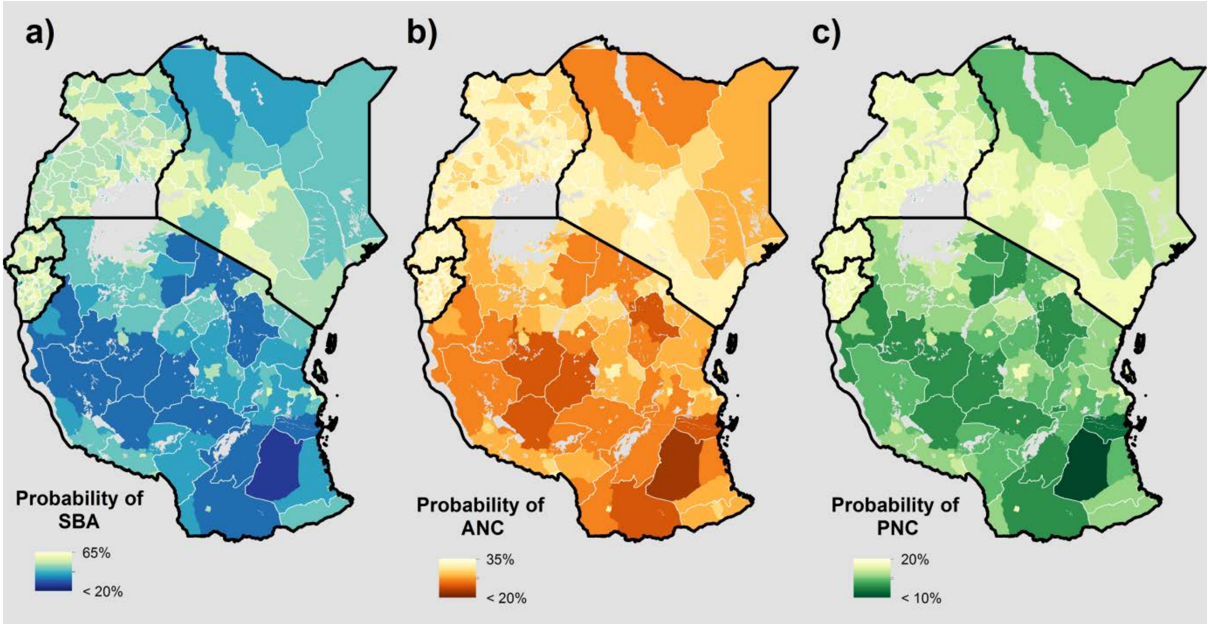


Figure 4.6 Births adjusted probability maps representing the probability of obtaining MNH care for a given birth at the administrative II unit. A) Delivery with a skilled birth attendant (SBA) present, B) Four or more antenatal care (ANC) visits at time of delivery, and C) Postnatal care (PNC) received within 48 hours of delivery.

Similar to the high-resolution surfaces, the observed ranges of probabilities varied between countries, with Kenya and Tanzania predominantly driving the scale of heterogeneity across outcomes. Regionally, the lowest probabilities of receiving MNH care occurred throughout northern Kenya and central Tanzania across outcomes. These probabilities generally tended to be higher in urban versus rural districts across countries and outcomes. Conversely, my model results showed Rwanda and Burundi to have consistently higher probabilities of a given birth receiving MNH care, as compared to Uganda, Tanzania and Kenya. Further, the range of these probabilities between administrative units varied less, suggesting less inequality between districts.

4.4.5 Model validation

To test the regression model's prediction power for utilisation of skilled birth attendance and antenatal/postnatal care, I performed a receiver operating characteristics (ROC) analysis. This analysis compares predicted prevalence to observed, and is used widely within diagnostic evaluation to validate regression models (Brooker et al., 2002). This method has been widely used within epidemiology and ecology, with recent applications in validating regression models within a spatial context (Clements et al., 2006a; Noor et al., 2008). The statistic used to evaluate ROC curves is known as the area under the curve (AUC), or a plot of sensitivity (or the ability to detect true positives) by 1-1 – specificity (or the ability to detect true negatives) (Clements et al., 2006a). The AUC statistic therefore represents the discriminatory power of the model in predicting true prevalence of a threshold, representing a trade-off between sensitivity and specificity (Fawcett, 2006). In general, higher AUC values represent increasing discriminatory ability of the model, or the ability to correctly classify predicted observations as receiving or not receiving a given service, with 0.9 representing a well-fitting model, 0.7 moderately-fitting model and 0.5 representing no better fit than what would be expected through random sampling (Clements et al., 2006a).

Figure 4.7 outlines the results of the ROC analysis, and provides metrics of the AUC-ROC, with the skilled birth attendance model performing relatively better than the ANC and PNC models. With an AUC value of 0.65, this model falls around values expected for a moderately well-fitting model, indicating a 65% probability that a woman observed with SBA had a higher estimated probability of SBA than a woman without SBA, for a random pair of women with and without the outcome (Clements et al., 2006a). The models representing antenatal care and postnatal care, however, were substantially less well-fitting, with AUC values of 0.55 and 0.57, respectively. While these models are better than what would be expected by random chance, these results suggest different factors may be driving SBA utilisation, as compared to ANC and PNC, and that the latter two outcomes should be explored in further detail to better predict their use.

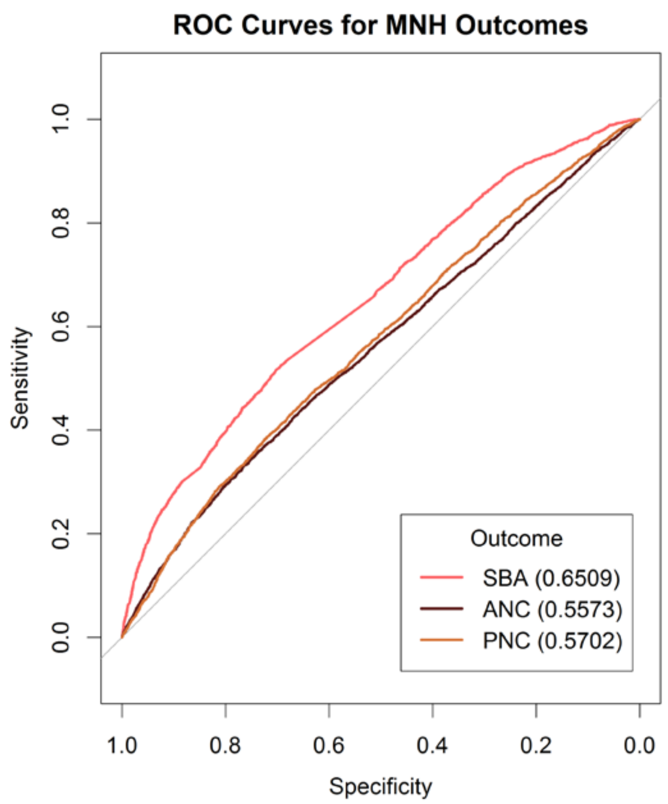


Figure 4.7 ROC curves for skilled birth attendance (SBA), antenatal care (ANC), and postnatal care (PNC) models, with associated area under the curve (AUC) metrics.

4.5 Discussion

Spatial inequalities in utilisation of MNH care continue to persist among low- and middle-income countries, particularly among skilled birth attendance and antenatal care coverage, and targeting spatial pockets of low utilisation will be critical for future health interventions (WHO, 2015a). A nuanced understanding of how geographic accessibility influences uptake of MNH care at a very fine spatial resolution will be key to identify and reduce these inequalities and alleviate coverage gaps. Here, I have highlighted the emergent spatial patterns of MNH care resulting from geographic accessibility at a high-resolution scale, and presented probabilities of obtaining MNH care for a given birth at the sub-national level. The spatial patterns revealed have important policy implications for informing allocation of future intervention efforts to target the most disadvantaged women and riskiest pregnancies. As these analyses highlight areas of low geographic accessibility, the presented results could help target not only health-related resources, but also future development more generally, including road networks and other transportation-related infrastructure.

Overall, I found that disparities exist in obtaining MNH care across wealth, education, and levels of rurality, and that decreased accessibility to the nearest health facility resulted in the widest disparities in obtaining care across the spectrum of pregnancy (Table 4.2). These findings are in line with previous studies, further establishing that barriers in deciding how, when, and even whether to seek care are greatest for uneducated, remote women in poverty (Barros et al., 2012; De Allegri et al., 2011; Gething et al., 2012). Regionally, I found that Kenya and Tanzania had the strongest patterns of spatial heterogeneity in the observed outcomes and generally lower probabilities of obtaining all types of care, with the lowest probabilities observed throughout rural districts in northern Kenya and central Tanzania. Conversely, I found Rwanda and Burundi to have generally higher probabilities of obtaining care, as compared to Tanzania, Kenya, and Uganda. This trend could be due in part to the relative density of facilities available, while more remote areas of Kenya and Tanzania had comparatively less facilities and primary or secondary road networks. This pattern also occurred sub-nationally, as I observed higher probabilities of obtaining care in urban versus rural districts, indicating infrastructure density is important in increasing MNH care coverage.

These findings suggest the allocation of funds focused on supporting increased infrastructure, such as buildings, equipment, and health workers, should appropriately reflect the demography and epidemiology of the area. These analyses could help to direct the flow of such resources, by highlighting areas and populations where care utilisation rates are lowest. While such infrastructure can improve geographic impedance and therefore accessibility, placement of primary health facilities offering comprehensive obstetric care or maternity waiting homes in these particularly resource-poor areas will ultimately be critical in reducing adverse MNH outcomes such as maternal and neonatal mortality (Gabrysch et al., 2011). Specifically, my results highlight northern Turkana, Samburu, Marsabit, Wajir, and Mandera districts in Kenya and central Rufiji and Liwale districts in Tanzania as key targets for increased coverage of facilities offering maternity care and construction of better road networks and transportation services. However, because these analyses did not capture information on use of lower tier facilities, referral networks, or community health workers linked to larger health facilities, MNH care utilisation in these areas may artificially be low. Therefore, to promote a more accurate representation of facility coverage in these areas, future data collection efforts should focus on areas of low geographic accessibility, capturing services provided and quality of services.

Future research should explicitly compare health systems throughout these countries, particularly in Rwanda and Burundi, to understand why MNH care performance is comparatively better in some countries as opposed to others. In particular, previous studies have noted that while MNH outcomes such as neonatal mortality are positively correlated with distance to closest health facility, health facility placement may already be saturated in countries that have prioritised improving facility coverage (Målqvist et al., 2010). In such cases, development of existing infrastructure, including continued support and education opportunities for community health workers, improved road networks and public transportation, and increased availability of comprehensive obstetric facilities or maternity waiting homes may ultimately prove effective in alleviating geographic accessibility as a barrier to accessing maternal health services. Finally, to promote a more nuanced and accurate understanding of geographic accessibility, future data collection efforts should aim to capture information on specific health facility used during pregnancy and birth, mode of transportation used to access these facilities, as well as self-reported travel time to these facilities.

4.5.1 Limitations

These analyses are subject to several limitations. Firstly, by excluding dispensaries from the analyses, it is possible that I incorrectly identify some women as having more difficulty in obtaining MNH care than is actually the case. However, I chose to be overly conservative in my modelling efforts by excluding these facilities, to avoid incorrectly assuming that a woman would have access to MNH services that are not actually there. Secondly, I use self-reported MNH outcomes and definitions, which may vary from country to country and may be subject to recall bias. This limitation explicitly impacts skilled birth attendance analyses, as some women may be unaware of what type of attendant was present at delivery, and countries may further define “skilled attendants” differently. While I limited my analyses of skilled attendance only to doctors, nurses and midwives, it is possible countries may define nurses and midwives variably. Future studies should ensure that definitions can be standardized on a multi-national level, and examine impacts of these definitions on model results. Thirdly, I assumed in my analyses that women would obtain care by travelling to the nearest health facility to their house. This often does not occur in reality, however, and is influenced by a host of individual and systematic factors, which may include, among others, the use of multiple facilities to obtain care via referral networks, the quality of care provided at the facility, and individual perception of the facility (De Allegri et al., 2011). Future work should more explicitly examine respondents’ actual use of health facilities, and explore key factors explaining where a woman decides to obtain care. Finally, my analyses were limited temporally by survey availability. Specifically, with data ranging over a 4-year span throughout the study countries, and gathering information on births in the previous 5 years, it is possible, that these results may no longer reflect the current state of maternal and newborn health in some countries. Future analyses should examine change in utilisation of MNH care over time, and use more recent datasets where available.

4.6 Conclusions

Inequalities in obtaining MNH care continue to persist, despite progress in increasing coverage and availability amongst the most vulnerable subgroups in the world. Spatial disaggregation of MNH data and a nuanced understanding of the geographic processes driving these disparities will be critical to continue this progress and accelerate achievement of SDG goals to reduce health disparities among all. Here, I spatially modelled the probability of several MNH outcomes at both high-resolution and policy relevant scales to highlight spatial patterns in accessibility and sub-national inequalities in MNH care utilisation throughout central East Africa. I found that disparities exist across the socioeconomic spectrum, with the widest disparities observed in geographic accessibility to health facilities, particularly among skilled birth attendance. The results of these analyses demonstrate how spatial approaches can be used to measure and identify spatial pockets of historically overlooked inequalities, thereby strategically informing policy efforts and promoting evidence-based decision-making. These findings are particularly pertinent to the East African Community in its efforts to accelerate progress in women's, children's and adolescent's health and equity within the framework of the SDGs.

4.7 Acknowledgements

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4.8 Intellectual contribution

The author list for this published work is as follows: Ruktanonchai CW, Ruktanonchai NW, Pezzulo C, Alegana VA, Bosco C, Nove A, Lopes S, Bytyqi A, Ayiko R, Charles A, Lambert N, Msechu E, Matthews Z, Tatem AJ. CWR conceived of the study framework and methods for this study, performed all data management and analysis, generated all study visualizations and results interpretations, and wrote and prepared the manuscript for journal submission. NWR, CB, CP, and VA contributed insight and feedback into the statistical and geographical analysis for this study. AN, SL, RA, and AC provided feedback on broad implications of study findings. ZM and AJT supervised CWR during production of this manuscript, and oversaw that methods and analysis were being executed within a sound and scientifically rigorous framework. RA, AC, NL, EM, and EK were involved with providing resources for this study, including country-specific datasets. All authors reviewed the manuscript and provided feedback before final publication.

Chapter 5: Temporal trends in spatial inequalities of maternal and newborn health services among four East African countries, 1999 – 2015

5.1 Abstract

Sub-Saharan Africa continues to account for the highest regional maternal mortality ratio (MMR) in the world, at just under 550 maternal deaths per 100,000 live births in 2015, compared to a global rate of 216 deaths. Spatial inequalities in access to life-saving maternal and newborn health (MNH) services persist within sub-Saharan Africa, however, with varied improvement over the past two decades. While previous research within the East African Community (EAC) region has examined utilisation of MNH care as an emergent property of geographic accessibility, no research has examined how these spatial inequalities have evolved over time at similar spatial scales.

Here, I analyse temporal trends of spatial inequalities in utilisation of antenatal care (ANC), skilled birth attendance (SBA), and postnatal care (PNC) among four East African countries. Specifically, I use Bayesian spatial statistics to generate district-level estimates of these services for several time points using Demographic and Health Surveys data in Kenya, Tanzania, Rwanda, and Uganda. I examine temporal trends of both absolute and relative indices over time, including the absolute difference between estimates, as well as change in performance ratios of the best-to-worst performing districts per country.

Across all countries, I find the greatest spatial equality in ANC, while SBA and PNC tended to have greater spatial variability. In particular, Rwanda represents the only country to consistently increase coverage and reduce spatial inequalities across all services. Conversely, Tanzania has noticeable reductions in ANC coverage throughout most of the country, with some areas experiencing as much as a 55% reduction. Encouragingly, however, I find that performance gaps between districts have generally decreased or remained stably low across all countries, suggesting countries are making improvements to reduce spatial inequalities in these services.

I find that while the region is generally making progress in reducing spatial gaps across districts, improvement in PNC coverage has stagnated, and should be monitored closely over the coming decades. This study is the first to report temporal trends in district-level estimates in MNH services across the EAC region, and these findings establish an important baseline of evidence for the Sustainable Development Goal era.

5.2 Introduction

Substantial progress has been made in reducing global maternal mortality over the past three decades, and while total coverage of maternal health services may have increased over time, inequalities among those utilising these services have persisted (Boerma et al., 2008; Nguhiu et al., 2017). Sub-Saharan Africa continues to account for the highest regional maternal mortality ratio (MMR) in the world, at just under 550 maternal deaths per 100,000 live births in 2015, compared to a global rate of 216 deaths. Further, only four countries achieved the 75% reduction (Cabo Verde, Equatorial Guinea, Eritrea, and Rwanda) set out by Millennium Development Goal (MDG) 5a (WHO et al., 2015). These ratios mask underlying heterogeneity, however, with MMRs ranging from as low as 167 per 100,000 live births in Southern Africa, to as high as 675 deaths per 100,000 live births in Western Africa in 2015 (WHO et al., 2015). The greatest reduction in MMR between 1990 and 2015 occurred within the Eastern Africa sub-region (as defined by the United Nations' (UN) MDG groupings), with a 57% overall change and 3.4% average annual change (WHO, 2015a). However, even within this sub-region, countries falling in the East African Community (EAC) region (comprised in 2015 of Burundi, Kenya, Rwanda, Tanzania, and Uganda, with the addition of South Sudan in 2016) experienced varied improvement in preventing maternal deaths over the past two decades, with Rwanda representing the only country within the region to reach the MDG 5a target.

Reducing health inequalities in low- and middle-income countries has become an increasingly important and quantifiable objective in the post-2015 Sustainable Development Goals (SDG) agenda (Barros and Victora, 2013; WHO, 2015b). While there has been a renewed call for disaggregation of national level indicators, much research in maternal and newborn health (MNH) over the previous decades has focused on disaggregating health data by socioeconomic status such as wealth quintile and education status (Assaf and Pullum, 2016; Boerma et al., 2008; WHO, 2015a). The state of a woman's health depends not only on her education and income, however, but also on where she lives and the progress her country is making in addressing maternal and newborn health issues (WHO, 2015a). Over the coming decades, therefore, spatial and temporal disaggregation in addition to this continued socioeconomic disaggregation will be key to ensuring healthy lives and well-being for all across all ages. By disaggregating data across spatial, temporal and socioeconomic dimensions, health inequalities amongst subgroups may be highlighted, as well as how these inequalities have changed over time (WHO, 2015a).

Preventing the deaths of women and newborns ultimately requires delivery of timely and high quality service packages and interventions across the continuum of care, such as antenatal care, skilled birth attendance, and postnatal care (Kerber et al., 2007). Previous studies have examined temporal trends of child mortality (Golding et al., 2017) and health indicators such as education (Graetz et al., 2018) and child growth (Osgood-Zimmerman et al., 2018) at high spatial resolutions, but fewer studies have examined temporal trends in utilisation of key MNH services at similar spatial resolutions. Victora and colleagues (Victora et al., 2016) reported progress in maternal, newborn, and child survival through the Millennium Development Goal era, while more recently, child and maternal mortality estimates have been systematically reported at the global, regional and national scales (Alkema et al., 2016a; Black et al., 2010). Assaf and Pullum (Assaf and Pullum, 2016) further reported temporal trends in key MNH services disaggregated by socioeconomic indicators such as wealth and education; these studies, however, represent analysis performed at a provincial or national-level spatial scale, and potentially mask important variation at policy-relevant spatial scales, such as the district level.

Within the EAC region, previous research (C. W. Ruktanonchai et al., 2016) has examined utilisation of MNH services as an emergent property of accessibility, highlighting high-resolution inequalities in receiving care before, during, and after delivery. While these inequalities have been spatially disaggregated, no research has examined how these spatial inequalities have evolved over time at similar spatial scales. Further, estimates at a policy-meaningful level such as the district level remain limited, as data collected in-country tend to be limited by insufficient reporting, sampling bias, or other methodological challenges. Estimates of MNH service utilisation have historically relied on household surveys such as the Demographic and Health Surveys (DHS), but these are not typically representative below the national or regional level due to sample design (with some recent exceptions such as the 2015 Kenya DHS). This necessitates the use of spatial statistics, such as small area estimation techniques and geo-spatial modelling frameworks, to generate predictive estimates at smaller spatial levels, but these approaches also come with methodological considerations. Spatial interpolation methods using a Bayesian framework are one such application of predictive modelling, and represent an ideal opportunity to quantify uncertainty in estimates through posterior distributions (Gething et al., 2015). Briefly, a Bayesian framework generates a distribution of possible estimates, or posterior distribution, in which the “true” value may lie, and allows for reporting of standard distribution statistics, such as mean, median, standard deviation, and credibility interval. This is particularly valuable when reporting DHS data at a spatial scale different from that which the data were collected at, where the range of uncertainty may vary in more rural, less sampled areas (Gething et al., 2015; Neal et al., 2019).

Here, this study examines how prevalence of antenatal care (ANC), skilled birth attendance (SBA), and postnatal care (PNC) use has changed sub-nationally over time within the EAC region, using both absolute and relative measures of inequality. Barros and Victora (Barros and Victora, 2013) argue that reporting temporal trends of both absolute and relative measures of inequalities is essential, as these measures complement each other to provide a more comprehensive reflection of change in inequality over time. This paper therefore aims to generate estimates of ANC, SBA, and PNC ranging between 1999 and 2015 at a higher spatial resolution than has been previously reported. I examine temporal trends of absolute indices by visualising the difference in these estimates between the first and last time points available. I further aim to examine temporal trends of relative indices by quantifying how the gap between the best-to-worst performing administrative units has changed over time, as well as explore how the effect of space alone has changed in predicting utilisation of these services.

5.3 Methods

5.3.1 Data

To explore sub-national change in ANC, SBA, and PNC over time, I compiled data from DHS for Kenya, Tanzania, Rwanda, and Uganda for several time points available (see Table 5.1) using SAS version 9.4 software (SAS Institute Inc., 2013). To calculate estimates using DHS data at a spatial area smaller than those which are reported through the DHS program, information on spatial location of household surveys are necessary through global positioning system (GPS) coordinates (Gething et al., 2015). The DHS program provides this information for recent surveys at the cluster (an aggregate of households) level, which is then displaced to maintain participant confidentiality. To facilitate spatial interpolation, I therefore included only standard DHS surveys in these analyses with corresponding geo-located cluster data available. Of note, at the time these analyses were performed, Burundi contained a full DHS survey with associated GPS data for only one year, and therefore was not included in these analyses. I further restricted these analyses to women with births in the previous five years to generate estimates of MNH services. Table 5.1 displays the DHS survey characteristics, final sample size, and number of clusters used in these analyses. I mapped cluster locations using ArcGIS software (Environmental Systems Research Institute, 2014) and drew corresponding buffers of 2km and 5km around urban and rural locations (respectively) in order to minimize bias resulting from DHS displacement protocols, in accordance with DHS recommendations outlined by Burgert and colleagues (Burgert et al., 2013).

Table 5.1 DHS survey used in study analysis and characteristics.

Country	Citation	Survey Year	Survey Type	Clusters	Sample
Kenya	(Central Bureau of Statistics - CBS/Kenya et al., 2004)	2003	Standard DHS-IV	399	2,969
	(Kenya National Bureau of Statistics - KNBS et al., 2010)	2008/9	Standard DHS-V	397	3,054
	(Kenya National Bureau of Statistics et al., 2015)	2014	Standard DHS-VII	1,585	11,151
Rwanda	(Institut National de la Statistique du Rwanda - INSR and ORC Macro, 2006)	2005	Standard DHS-V	462	4,002
	(National Institute of Statistics of Rwanda - NISR et al., 2012)	2010	Standard DHS-VI	492	4,746
	(National Institute of Statistics of Rwanda et al., 2016)	2014/15	Standard DHS-VII	492	4,467
Tanzania	(National Bureau of Statistics/Tanzania and Macro International, 2000)	1999	Standard DHS-IV	176	1,504
	(National Bureau of Statistics - NBS/Tanzania and ICF Macro, 2011)	2010	Standard DHS-VI	475	4,019
	(Ministry of Health et al., 2016)	2015/16	Standard DHS-VII	608	5,288
Uganda	(Uganda Bureau of Statistics - UBOS and ORC Macro, 2001)	2000/1	Standard DHS-IV	266	2,790
	(Uganda Bureau of Statistics - UBOS and Macro International, 2007)	2006	Standard DHS-V	336	3,420
	(Uganda Bureau of Statistics - UBOS and ICF International, 2012)	2011	Standard DHS-VI	400	3,645

Finally, to allow for temporal analysis of model outcomes and spatial comparison, clusters at each survey year available were spatially linked to the most recent administrative II unit available for each country using ArcGIS software. Briefly, administrative units are subnational geographic areas used for administrative or political purposes, such as districts, regions, counties and states. In the United States, for example, administrative I units correspond to the state level, while administrative II units correspond to counties (with the exception of two states). Because the word for these geographic areas may vary substantially by country (i.e., district, county, borough, etc.), the administrative II-unit level used in these analyses is hereby referred to as the ‘district’ level for the purposes of this paper. I spatially linked survey data to the most current district boundaries available for each country, as both DHS and political boundaries in many of the study countries have changed since 1999, preventing direct comparison of change over time. Further, by disaggregating each country at a uniform district level, spatial comparisons across countries could be standardized.

5.3.2 Absolute indices of temporal change

I employed a Bayesian inference framework using the Integrated Nested Laplace Approximation (INLA) package (Rue et al., 2009) in R (R Development Core Team, 2017) to spatially interpolate coverage estimates for ANC, SBA, and PNC at the district level throughout the study countries. Specifically, I used the Besag-York-Mollier (BYM-2) class of models within the INLA package, which have been shown to be particularly useful in mapping disease, as unstructured spatial effects can be added to account for region-specific variation (Niragire et al., 2015; Riebler et al., 2016). The model was therefore defined as

$$\text{logit}(p_{ij}) = \beta_0 + \beta_1 x_{ij} + \beta_2 x_{ij} \dots \beta_5 x_{ij} + f_{spat}(admin_j)$$

where logit(p_{ij}) represents the odds of a woman's most recent birth, *i*, in administrative unit, *j*, obtaining the corresponding health service (SBA, ANC, and PNC); $\beta_0 + \beta_1 x_{ij} + \beta_2 x_{ij} \dots \beta_5 x_{ij}$ represents the fixed effects of the model as described below; and $f_{spat}(admin_j)$ represents the structured spatial effect of administrative unit, *j*, as a combination of both the structured and unstructured random effects, defined as

$$f_{spat}(admin_j) = f_{struc}(admin_j) + f_{unstruc}(admin_j)$$

For these analyses, I assumed an uninformative prior distribution on model parameters to allow the data to drive model results, as no previous literature or data exist at this level for each year to inform expectations of the spatial distribution of model outcomes. By assuming uninformative priors across all models at each time point available, this allowed for better comparison of model results. Similar approaches have been used previously (Neal et al., 2019) with adolescent health indicators using DHS data. The model outputs generated by this method represent a posterior distribution of possible estimates for each outcome at the district level. The mean of this distribution can therefore be taken to represent a point estimate for each geographic unit, while also allowing for reporting of standard distribution statistics (such as standard deviation and credibility intervals) which can be used to represent uncertainty surrounding each estimate. To visualize the absolute change over time among these indicators, I compared estimates for each country between the first and last surveys available.

Binary model outcomes included SBA, ANC, and PNC, while fixed model effects included urban/rural residence, education status, wealth quintile, maternal age, and parity, which have been defined in previous literature as important predictors of MNH services (Gabrysch and Campbell, 2009a; Neal et al., 2015; C. W. Ruktanonchai et al., 2016). To maintain comparability across countries, I defined skilled birth attendance as births attended by a doctor, nurse, or auxiliary midwife for the most recent birth available. Antenatal care was defined amongst the most recent birth as 4+ antenatal care visits, while postnatal care was defined as a maternal check-up within 48 hours of the most recent delivery by a health professional (doctor, nurse, or auxiliary midwife). For deliveries occurring at a health facility, I assumed postnatal care was provided by a health professional (as defined above) unless otherwise specified by the data. Lastly, I report model fit through the Deviance Information Criterion (DIC) values, which provide a measure of goodness-of-fit for Bayesian models, while adjusting for model complexity and effective number of parameters, with smaller DIC values representing better fitting models (Spiegelhalter et al., 2002).

5.3.3 Relative indices of temporal change

I examined relative indices of temporal change by quantifying the ratio between best-versus-worst modelled estimates among districts, with larger values representing increased gaps in coverage between districts, and smaller values nearing one representing decreasing spatial inequality. I further examined the temporal trend of spatial effects by reporting univariate logistic odds ratio (OR) using the 'lme4' package in R software (Bates et al., 2014) for each outcome and time point available. Similar approaches have been used by researchers at the DHS program (Assaf and Pullum, 2016) to temporally examine socioeconomic inequalities such as wealth in MNH. These analyses have reported coefficients for the richest quintiles as compared to the poorest, with values overlapping zero representing no statistically significant difference in services as predicted by wealth. I similarly report coefficients for DHS region with the best-performing (or highest coverage) for each outcome, as compared to the worst-performing (or lowest coverage) region, representing temporal trends in spatial inequalities divorced of modelled estimates. Specifically, I defined coverage as the proportion of women in the sample accessing a given service—for example, 90% of women reporting skilled attendance at birth would correspond to 90% coverage for this indicator. DHS regions used for reference and coefficients reported are outlined in Table B.2 (see Appendix B). More information on region boundaries used by the DHS can be found at spatialdata.dhsprogram.com/boundaries. In these analyses, values overlapping zero represent no significant effect of space in predicting odds of MNH outcome use, while increasing values represent a greater effect of space alone in predicting service utilisation.

5.3.4 Model validation

To validate model performance, I employed an out-of-sample validation technique, where 25% of the data were removed for validation purposes, while the remaining 75% were used for model training. I report standard validation statistics, including mean absolute error (MAE), mean square error (MSE), and pseudo-R2. Previous studies (Bosco et al., 2017; Gething et al., 2015) have employed similar statistics when interpolating surfaces using DHS data, and represent information on model precision, model bias, and variance explained, respectively.

5.3.5 Ethics approval

Ethics approval for this study was submitted and approved through the University of Southampton Ethics and Research Governance Council (ethics approval ID 26474). The data used in these analyses were obtained from the Demographic and Health Surveys (DHS) Program, which makes global health and demographic data confidentially and freely available to researchers across the world. More information on how the DHS program conducts the Informed Consent process can be found at https://dhsprogram.com/What-We-Do/Protecting-the-Privacy-of-DHS-Survey-Respondents.cfm.

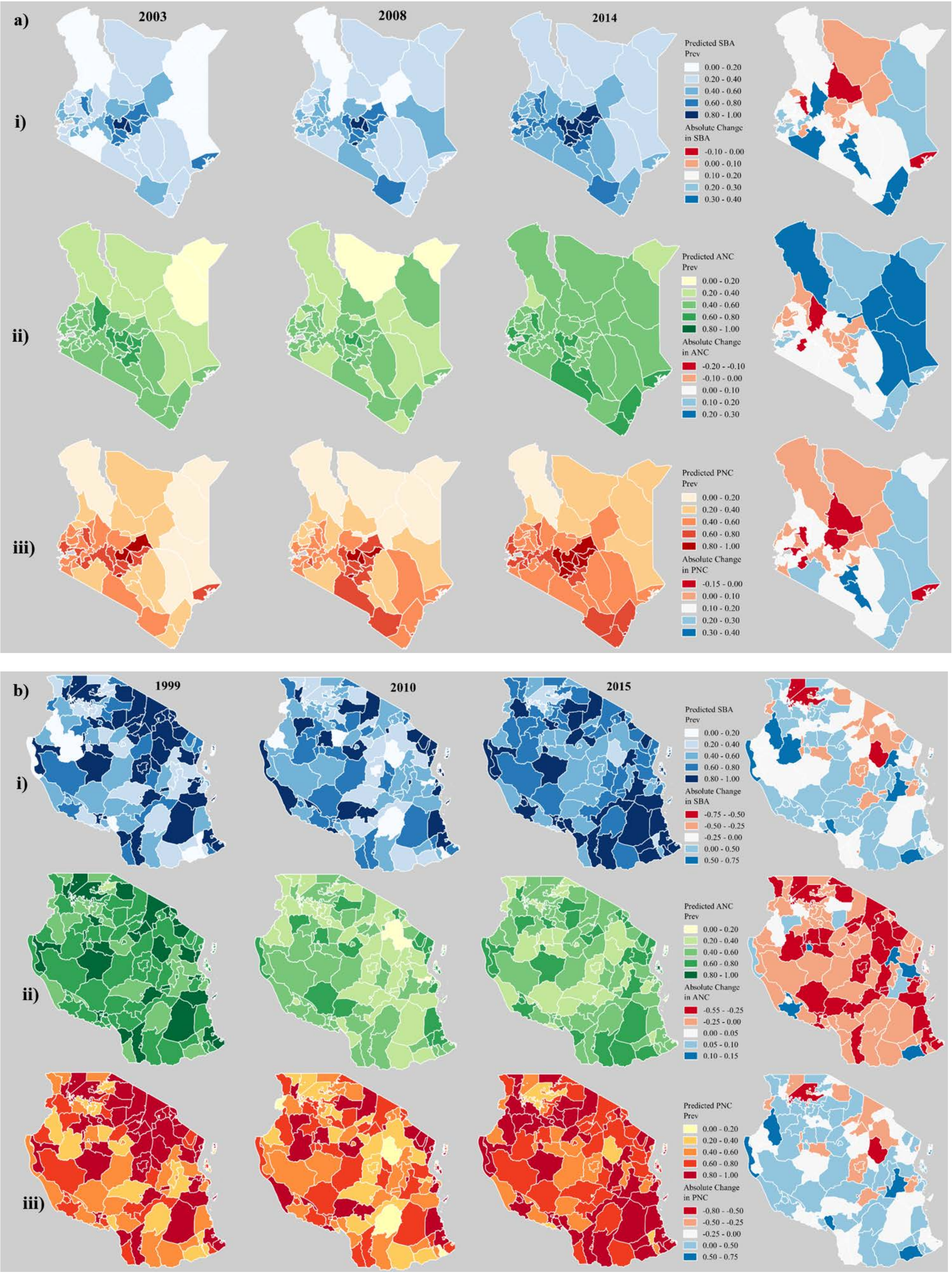
5.4 Results

5.4.1 Absolute indices of temporal change

Figures 5.1a – d show modelled prevalence estimates of skilled birth attendance (i), antenatal care (ii), and postnatal care (iii) at the district level, and corresponding absolute change over time in these estimates between the first and last time points available. For absolute change over time, areas in blue indicate an increasing prevalence estimates between the first and last time points, while areas in white represent a small, but increasing change over time, and areas in red indicate decreasing prevalence estimates over time. The corresponding absolute change estimates for each districts are labelled and ordered increasingly in figures B.3 – B.6 (see Appendix B), to facilitate visualisation of greatest to least improvement for each district.

Rwanda (Figure 5.1c) represented the only country with exclusively increasing prevalence over time amongst all three services, with as much as 85% increases in SBA for some districts and nearing universal coverage for both SBA and PNC. While more moderate gains were seen for antenatal care, every area within the country saw increases in prevalence, ranging to as high as a 60% increase. Equally encouraging, the greatest increases for Kenya (Figure 5.1a) were primarily localized within the eastern region of Kenya, which has historically shown higher levels of wealth inequality and more adverse maternal health outcomes as compared to the rest of the country, particularly in the northern parts of the region (Assaf and Pullum, 2016). Increases in this area were also seen amongst skilled birth attendance and postnatal care, however these were comparatively more conservative increases.

Conversely, Tanzania (Figure 5.1b) had noticeable reductions in coverage throughout most of the country in utilisation of 4+ antenatal care visits, with some areas experiencing as much as a 55% reduction. This trend was predominantly driven by high coverage in ANC in 1999, which were substantially reduced in the 2010 and 2015 DHS surveys. This trend however, did not hold for skilled birth attendance and postnatal care, with much of the country experiencing improvement amongst these services. While Uganda (Figure 5.1d) experienced improvement in skilled birth attendance over time, it experienced equally substantial decreases or little to no improvement in antenatal care and postnatal care in Northern and central Uganda. Similar to Tanzania, these trends were predominantly driven by high estimates during the 2000 DHS, decreasing with the 2006 and 2011 surveys.


a)
2003
2008
2014
i)
ii)
iii)
Predicted SBA Prev
0.00 - 0.20
0.20 - 0.40
0.40 - 0.60
0.60 - 0.80
0.80 - 1.00
Absolute Change in SBA
-0.10 - 0.00
0.00 - 0.10
0.10 - 0.20
0.20 - 0.30
0.30 - 0.40
Predicted ANC Prev
0.00 - 0.20
0.20 - 0.40
0.40 - 0.60
0.60 - 0.80
0.80 - 1.00
Absolute Change in ANC
-0.20 - -0.10
-0.10 - 0.00
0.00 - 0.10
0.10 - 0.20
0.20 - 0.30
Predicted PNC Prev
0.00 - 0.20
0.20 - 0.40
0.40 - 0.60
0.60 - 0.80
0.80 - 1.00
Absolute Change in PNC
-0.15 - 0.00
0.00 - 0.10
0.10 - 0.20
0.20 - 0.30
0.30 - 0.40
b)
1999
2010
2015
i)
ii)
iii)
Predicted SBA Prev
0.00 - 0.20
0.20 - 0.40
0.40 - 0.60
0.60 - 0.80
0.80 - 1.00
Absolute Change in SBA
-0.75 - -0.50
-0.50 - -0.25
-0.25 - 0.00
0.00 - 0.50
0.50 - 0.75
Predicted ANC Prev
0.00 - 0.20
0.20 - 0.40
0.40 - 0.60
0.60 - 0.80
0.80 - 1.00
Absolute Change in ANC
-0.55 - -0.25
-0.25 - 0.00
0.00 - 0.05
0.05 - 0.10
0.10 - 0.15
Predicted PNC Prev
0.00 - 0.20
0.20 - 0.40
0.40 - 0.60
0.60 - 0.80
0.80 - 1.00
Absolute Change in PNC
-0.80 - -0.50
-0.50 - -0.25
-0.25 - 0.00
0.00 - 0.50
0.50 - 0.75

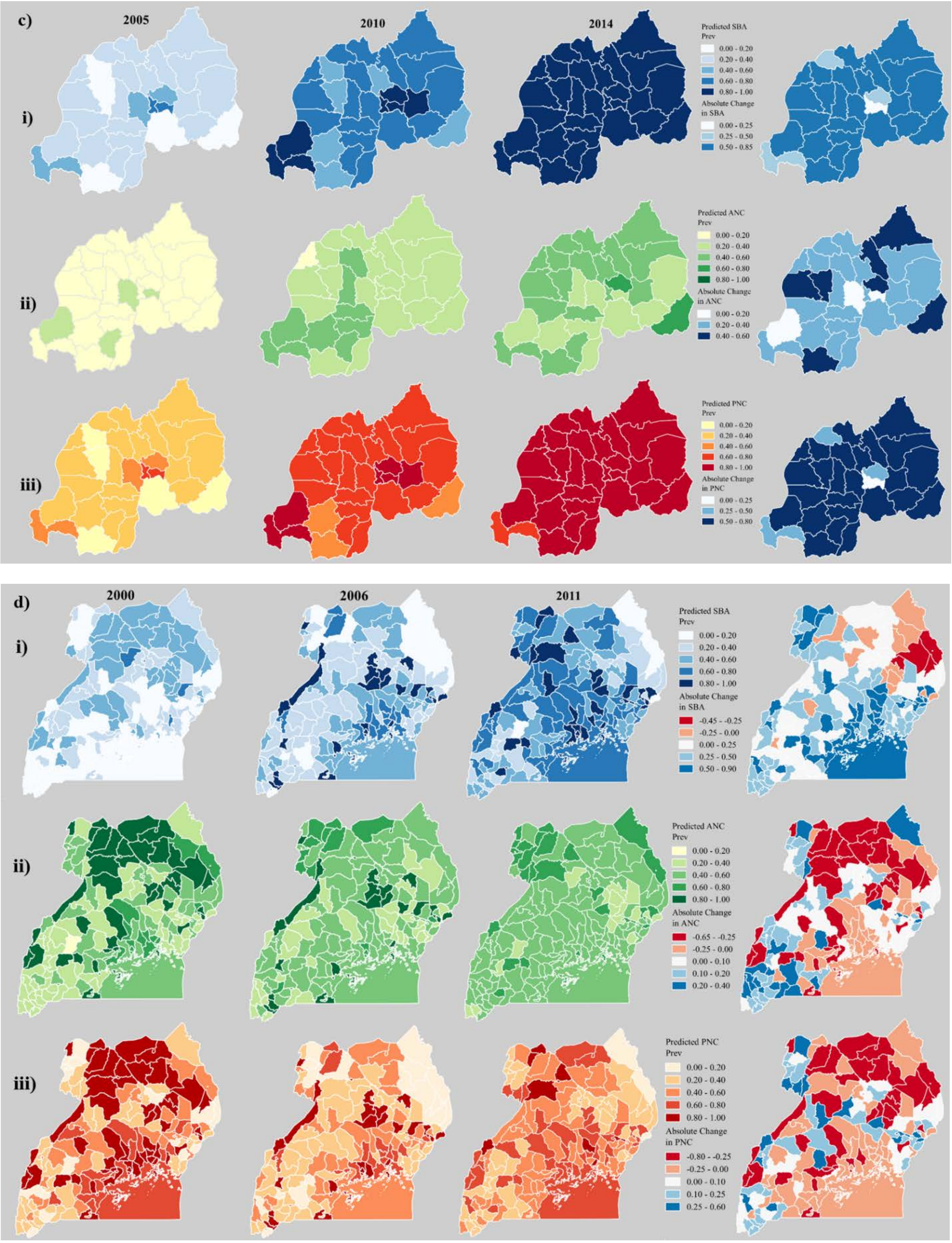


Figure 5.1 Predicted prevalence and absolute change in i) skilled birth attendance (blue), ii) 4+ antenatal care visits (green), and iii) postnatal check-up within 48 hours (red) among administrative II units, among DHS data in a) Kenya, 2003 – 2014 b) Tanzania, 1999 – 2015, c) Rwanda, 2005 – 2014, and d) Uganda, 2000 – 2011.

Model outcomes, estimates and fit are outlined in Table B.3 (see Appendix B). Figure 5.2 compares model fits across outcomes by country, as measured by the DIC. Of note, the y-axis for DIC values varies by country, as these values should not be compared between countries. In general, SBA and PNC models tended to perform better as compared to ANC models, with the exception of the most recent models in Uganda, where models all performed similarly. DIC values also tended to increase over time, possibly due to increasing sample size (see Table B.3), with the exception of Rwanda. Models in Rwanda tended to perform similarly in 2010, but had more variability in 2005 and 2014. However, this variability only ranged between 30 points, similar to models in other countries.

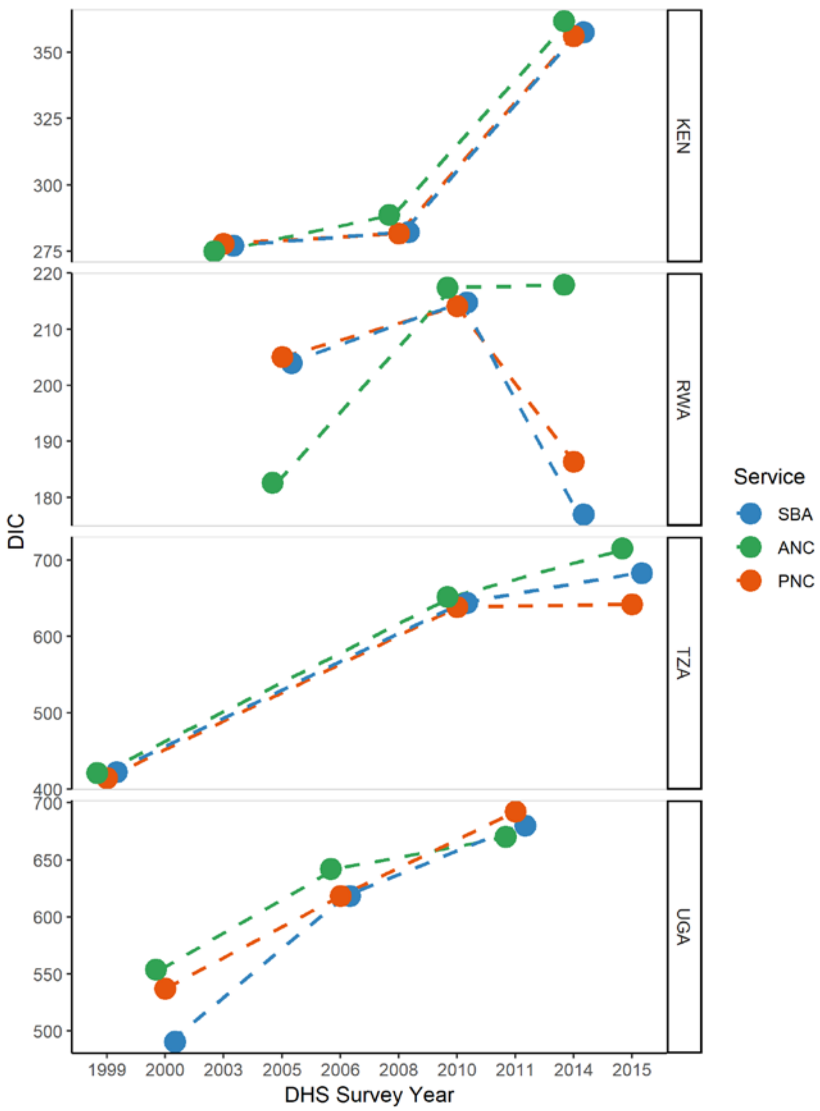


Figure 5.2 DIC values for skilled birth attendance (blue), 4+ antenatal care visits (green), and postnatal care (red) models, by country, DHS data, 1999 – 2015.

5.4.2 Relative indices of temporal change

Figure 5.3 shows performance ratios of each outcome, reflecting the relative gap within countries between the district with the highest-versus-lowest prevalence estimates over time. Values closer to one therefore represent spatial homogeneity in coverage, while higher values represent more disparate gaps within countries amongst services. Across all countries, the lowest ratios tended to be among ANC, with the exception of Rwanda, while SBA and PNC tended to have greater ratios between the highest and lowest district estimates, suggesting greater spatial heterogeneity. Generally, ratios have typically decreased or remained stably low over time across all countries.

Historically, Rwanda had relatively small ratios that decreased over time, while Kenya had the highest inequalities in SBA, these were substantially reduced over time. Tanzania equally experienced reductions in SBA and PNC, but saw little to no change in ANC over time as it was already relatively low. Uganda also saw substantial improvement in reducing disparities over time for SBA and PNC (despite an increasing ratio for the year 2005), nearly halving the SBA ratio from 25 to 12 within the span of a decade. Regardless, the most recent ratios in Kenya and Tanzania across service utilisation still remained around 5, meaning the best performing region of the country had coverage about 5-times higher than the corresponding lowest region. Further, while Uganda saw improvement across services, ratios amongst SBA and PNC still represent the highest ratios across the region, suggesting there is still need for further improvement.

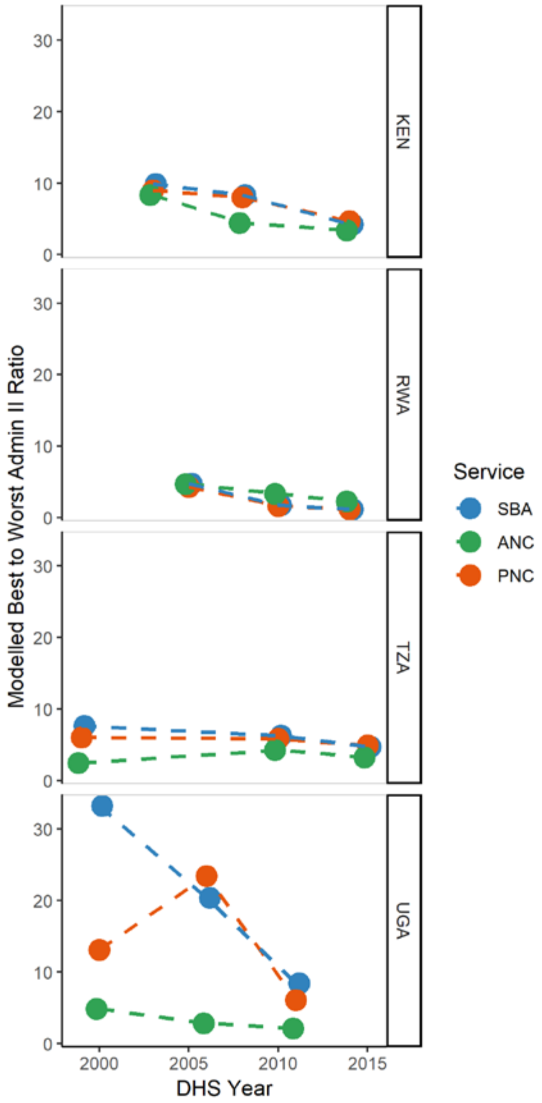


Figure 5.3 Ratio of modelled best-to-worst performing administrative II units over time for skilled birth attendance (blue), 4+ antenatal care visits (green), and postnatal care (red), by country, DHS data, 1999 - 2015.

Lastly, Figure 5.4 shows results of the unadjusted logistic odds ratio, plotting coefficients of the DHS region with the highest corresponding coverage as compared to the region with the lowest coverage as reference. Positive, significant coefficients imply a statistically significant effect of space exists, while estimates spanning zero imply no significant difference across regions in likelihood of utilising SBA, ANC, or PNC. Historically, Rwanda saw high levels of inequality in utilising MNH services by space, but univariate logistic odds results suggest the effect of space has been substantially reduced over the decades, representing the country with the lowest odds ratios across services amongst the most recent survey. Of note, the odds of obtaining PNC in 2010 was negative, implying odds in the best performing regions were actually reduced as compared to the worst performing region. Kenya further saw decreasing ORs over time for both ANC and PNC, but saw little improvement for SBA, with Nairobi having 2 to 3 times higher odds of utilising skilled birth attendance over time as compared to the North Eastern region. Despite this improvement, Kenya's ORs remain amongst the highest across the region, in combination with Tanzania.

In contrast to Rwanda and Kenya's decreasing trends in ORs, Tanzania and Uganda had substantial variability in ORs over time. Encouragingly, the effect of space is relatively low in Uganda amongst ANC and PNC, but has increased over time for SBA. However, the odds of obtaining SBA amongst the DHS region with the highest SBA coverage versus the lowest was just over 1 in 2011, representing the lowest coefficient for SBA outside of Rwanda. Tanzania also saw an increasing effect of space over time for PNC, and further has high ORs along with Kenya.

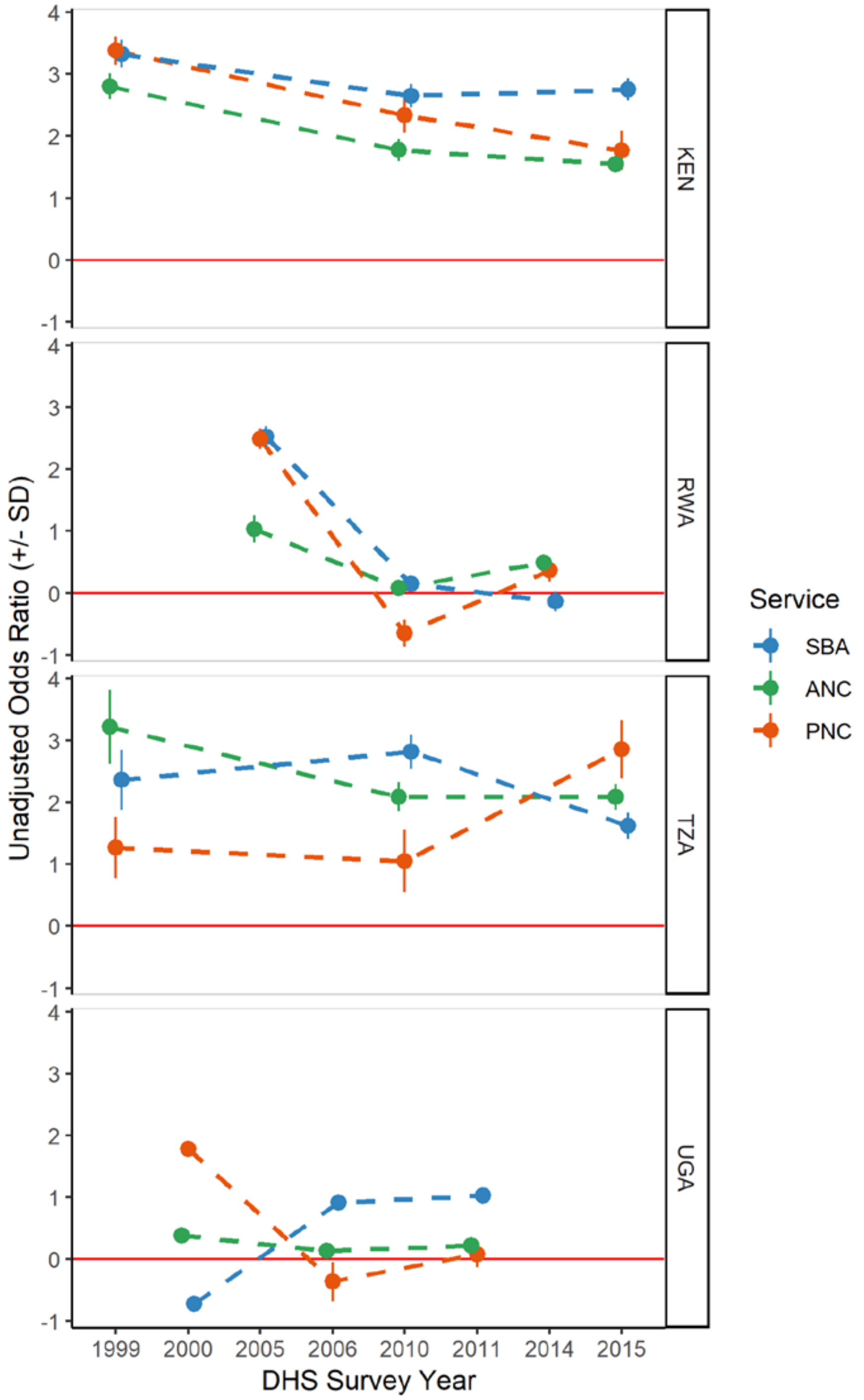


Figure 5.4 Unadjusted odds ratio of skilled birth attendance (blue), 4+ antenatal care visits (green), and postnatal care (red) over time, with worst performing DHS region as reference, DHS data, 1999 – 2015.

5.4.3 Model validation

Model validation results are show in Table 5.2. Generally, model fit was greatest for all services in Kenya, ranging from 88.4% variance explained for ANC in 2008 to as high as 99.7% in 2014 for

SBA and PNC. Model fit was poorest for ANC in Uganda, with psudeo-R2 estimates of 0.138 and 0.239 for ANC in 2006 and 2014. In general, model fit was poorest for ANC for all years and countries, with the exception of Rwanda after 2010. Model precision and bias were predominantly uniform across countries, but was worst among Uganda models, potentially contributing to the low explained variance.

Table 5.2 Model validation results

Kenya				***Tanzania***			
	MSE	**MAE**	**Psuedo -R^2**		**MSE**	**MAE**	**Psuedo -R^2**
2003				*1999*			
SBA	0.0022	0.0344	0.949	**SBA**	0.0099	0.076	0.876
ANC	0.002	0.0337	0.925	**ANC**	0.0164	0.101	0.544
PNC	0.0019	0.0286	0.960	**PNC**	0.0098	0.0763	0.855
2008				*2010*			
SBA	0.0013	0.027	0.973	**SBA**	0.0049	0.0501	0.929
ANC	0.0021	0.0357	0.884	**ANC**	0.0067	0.0580	0.796
PNC	0.0017	0.030	0.967	**PNC**	0.0041	0.0455	0.938
2014				*2015*			
SBA	0.00009	0.0073	0.997	**SBA**	0.0043	0.0441	0.901
ANC	0.0001	0.0095	0.987	**ANC**	0.006	0.055	0.787
PNC	0.00008	0.0072	0.997	**PNC**	0.004	0.0376	0.925
Rwanda				***Uganda***			
	MSE	**MAE**	**Psuedo -R^2**		**MSE**	**MAE**	**Psuedo -R^2**
2005				*2000*			
SBA	0.005	0.0538	0.80	**SBA**	0.024	0.115	0.656
ANC	0.003	0.0404	0.475	**ANC**	0.04	0.151	0.529
PNC	0.0043	0.0517	0.816	**PNC**	0.035	0.140	0.702
2010				*2006*			
SBA	0.002	0.033	0.887	**SBA**	0.030	0.127	0.657
ANC	0.001	0.0300	0.905	**ANC**	0.054	0.173	0.138
PNC	0.001	0.0326	0.877	**PNC**	0.028	0.124	0.684
2014				*2011*			
SBA	0.0008	0.024	0.704	**SBA**	0.025	0.119	0.678
ANC	0.0023	0.0365	0.795	**ANC**	0.050	0.171	0.239
PNC	0.0010	0.0270	0.738	**PNC**	0.033	0.136	0.534

5.5 Discussion

The vast majority of maternal deaths can be prevented through routine health services, such as antenatal care and skilled birth attendance, or treated through timely interventions and prevention (Bailey et al., 2006). Within developing countries, however, the use of key life-saving interventions can be limited and inequitably distributed, and varies by country-specific contextual issues, such as funding and organization of health care or social and cultural issues (Say and Raine, 2007). Continuing MDG progress in preventing maternal deaths and achieving SDG targets of "ensuring healthy lives and promoting well-being for all at all ages" (WHO, 2015b) will require more resolved spatial, temporal, and demographic information to identify and monitor persistent health inequalities. Examining temporal change in spatial inequalities of maternal health service use, however, requires reporting of both absolute and relative indices, as such measures often interact with each other synergistically and therefore require joint interpretation (Barros and Victora, 2013).

Here, I found that Rwanda was the only country to make substantial progress in both absolute and relative measures, increasing coverage amongst all services and reducing relative inequalities. Importantly, Rwanda had historically low relative inequality in service coverage (Figure 5.3), suggesting that the increases in service coverage seen in Rwanda over the decades were experienced in spatially equitable manner, with most of the country improving together. These results are in line with previous findings, given that Rwanda was the only country in the region to achieve the MDG target 5a (reduce MMR by 75% between 1990 and 2015) (WHO et al., 2015). After experiencing a devastating genocide in the mid-90s, Rwanda radically re-developed their health system, aimed at: 1) coordinating policy with external donors and government aid; 2) implementation of national-level health insurance; and, 3) introduction of a performance-based pay system for health workers (Logie et al., 2008). This commitment to improving health across the country translated into a nearly 78% reduction in MMR throughout the MDG era, as well as a substantial reduction in under-5 mortality (Golding et al., 2017), and may contribute to the findings outlined in this study.

I found that Uganda has experienced both absolute and relative improvement over time in SBA across most of the country, while improvement in PNC and ANC lagged, particularly in the northern region. Previous studies (Ayiko et al., 2009) have similarly found poor outcomes in under-five mortality in this area, attributing the trend partly to the nearly two decades of armed conflict in the region which disrupted health systems and impacted the socio-economic stability across the region. Other studies (Parkhurst et al., 2005) have found that while skilled birth attendance is high, other key MNH metrics such as vaccine coverage lag, and suggest that quality of care in Uganda is insufficient, resulting in delayed emergency treatment and insufficient supplies. Further studies (Roberts et al., 2015) have found minimal increases over time in MNH indicators requiring multiple contacts with the health system, such as 4+ antenatal care visits, consistent with these findings. This suggests that while Uganda has rapidly increased the number and scale of maternal health interventions across the country, some areas (particularly in the northern regions) have historically and systematically lagged behind and require more deliberate efforts and focused interventions to further close the gap in MNH inequalities (Ayiko et al., 2009).

In Tanzania, I found a notable absolute decrease in coverage of 4+ antenatal care visits between 1999 and 2010, with little change through 2015. Regardless, northern and north-eastern Tanzania experienced a relative reduction over time across all services, suggesting the possibility that these areas are being left behind in improving access to or utilisation of maternal health services. Tanzania achieved MDG targets for child survival, and while previous studies (Hanson et al., 2017) have noted that geographic inequalities in access to primary care at childbirth have been reduced, inequalities persist in actual hospital-based deliveries and antenatal care. These findings are in line with these studies (Armstrong et al., 2016) suggesting maternal survival has lagged behind due to low coverage of maternal health services, with rural women bearing a disproportionate burden of risk. Examining potential bottlenecks to explain these patterns, Armstrong et al. (Armstrong et al., 2016) suggested that Tanzania must make progress in all four “benchmarks” of quality health systems, as the country experienced low density of health workers, poor availability of supplies at health facilities, and low levels of health financing, particularly in the Lake and Western districts. Despite this, I found ratios between districts generally decreased slightly, suggesting some progress is being made in reducing inequalities. Further, I found the odds of region alone in predicting SBA substantially declined and is remaining relatively stable with ANC, yet is noticeably increasing for PNC. These findings suggest that geographic inequalities in coverage of SBA are being reduced within country, but coverage in ANC and PNC must be followed closely and prioritized over the coming decades.

Finally, I found that Kenya experienced substantial improvement in absolute change of 4+ ANC visits over time, particularly with the eastern districts, but coverage in SBA and PNC decreased, particularly in the northern districts. I further found that while relative inequalities between districts are reducing across services, they still remain high compared to the rest of the region. Across the country, I also found that urban areas experienced substantially higher odds of obtaining MNH services (and particularly skilled birth attendance) as compared to rural areas, in line with previous research (Assaf and Pullum, 2016). Nguhiu et al. similarly found that while overall coverage of MNH interventions has steadily increased over time and maternal inequities decreased within Kenya, coverage of individual interventions including antenatal care and skilled birth attendance remained stubbornly low and inequitable, with ANC experiencing the most inequitable coverage (Nguhiu et al., 2017). They suggest that increased overall coverage may be linked to increasing per capita health expenditure within the country, as well as urbanization and expansion of lower level health facilities over the decades, but propose that interventions directed at those services lagging behind should be accordingly prioritised over the coming decades.

5.5.1 Limitations

As this work primarily utilises estimates generated using statistical inference, it is subject to several limitations, including survey and sampling errors inherent to DHS data. Particular to spatial interpolation at levels below the DHS region, these data were collected using methods representative at geographic units which are different from the measures I report, potentially resulting in model uncertainty and errors. However, the DHS program endorses use of geospatial interpolation methods such as Bayesian inference, particularly because of the ability to quantify this uncertainty in posterior distribution estimates (Gething et al., 2015). The DHS data is also subject to temporal biases, as it is collected at varying intervals between countries, and information on maternal services are collected for up to five years previous. This represents a potential time lag in temporal analyses, and the trends reported here may not represent the current picture of MNH service utilisation in these countries. Further, with some of the countries used in these analyses, the most recent DHS available is upwards of five years old, representing an important avenue for future analyses to continue to examine these trends using more recent data. Lastly, the actual hospital or health facility used for the services used was not included in these analyses, as the DHS does not report this information. This could potentially bias model results, as the hospital or health facility may be outside of the respondent's surveyed district. Actual health facility used should be included in future research if available, as well as cross-border movement.

While the scope of this paper is to report temporal trends in spatial inequalities of MNH service use over time, future work should aim to explain why these patterns are occurring to potentially offer insight into policy interventions aimed at maintaining progress to ensure no populations are left behind in accessing MNH services. Future research should examine factors at several socio-ecological levels, including the individual, cultural, and national level, as well as quality of care provided. Spatial context such as travel time to health facilities and actual health facilities used should also be taken into account (Makanga et al., 2016).

5.6 Conclusions

This study is the first to report model-based estimates at the district level for several time points across the EAC region, as well as report temporal trends in both absolute and relative measures of spatial inequalities. I found that relative inequality between districts have generally decreased or remained stably low over time across all countries, suggesting improvements are being made to reduce the gap between the geographic areas with the highest and lowest coverage in services. I further found that Rwanda in particular was successful in reducing relative inequalities over time, as well as increasing absolute coverage across all MNH services. Despite this progress, I found that relative measures of spatial inequalities across the region indicate that the effect of space is becoming more prominent over the decades among PNC in particular, suggesting this should be monitored closely throughout the SDG era and examined further with new sources of DHS data or other household surveys.

These analyses demonstrate how the use of spatial and temporal disaggregation methods can be used to monitor the evolution of health inequalities over the SDG period. These results highlight the need for continued disaggregation of these data over time, which will be key in improving health amongst all populations across the East African Community. Lastly, in-country uptake and adoption of GIS-enabled analytics facilitating concurrent temporal and spatial analysis of socio-economic, environmental and health systems level determinants will be key to development of precise policy actions for addressing areas with intractable health challenges and ensuring that SDG health targets are met by 2030.

5.7 Acknowledgements

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5.8 Intellectual contribution

The author list for this published work is as follows: Ruktanonchai CW, Nilsen K, Alegana VA, Bosco C, Ayiko R, Charles ASK, Matthews Z, Tatem AJ. CWR conceived of the study framework and methods for this study, performed all data management and analysis, generated all study visualizations and results interpretations, and wrote and prepared the manuscript for journal submission. CB, VA and KN contributed insight and feedback into the statistical and geographical analysis for this study. RA and AC provided feedback on broad implications of study findings relevant to the study region. ZM and AJT supervised CWR during production of this manuscript, and oversaw that methods and analysis were executed within a sound and scientifically rigorous framework. All authors reviewed the manuscript and provided feedback before final publication.

Chapter 6: Estimating uncertainty in geospatial modelling at multiple spatial resolutions: the pattern of delivery via caesarean section in Tanzania

6.1 Abstract

Visualising maternal and newborn health (MNH) outcomes at fine spatial resolutions is crucial to ensuring the most vulnerable women and children are not left behind in improving health. Disaggregated data on life-saving MNH interventions remain difficult to obtain, however, necessitating the use of Bayesian geostatistical models to map outcomes at small geographical areas. While these methods have improved model parameter estimates and precision among spatially correlated health outcomes and allowed for the quantification of uncertainty, few studies have examined the trade-off between higher spatial resolution modelling and how associated uncertainty propagates.

Here, I explore the trade-off between model outcomes and associated uncertainty at increasing spatial resolutions by quantifying the posterior distribution of delivery via c-section in Tanzania. Overall, in modelling delivery via c-section at multiple spatial resolutions, I demonstrate poverty to be negatively correlated across spatial resolutions, suggesting important disparities in obtaining life-saving obstetric surgery persist across sociodemographic factors. Lastly, I note that while uncertainty increased with higher spatial resolution input, model precision was best approximated at the highest spatial resolution, suggesting an important policy trade-off between identifying concealed spatial heterogeneities in health indicators.

6.2 Introduction

Achieving the Sustainable Development Goal aims laid out in 2015 necessitates measurement of health outcomes at small geographical areas to ensure 'no one left behind' (C. Edson Utazi et al., 2018b). With recent advancements in the collection and distribution of geo-located household surveys, such as those collected via the Demographic and Health Survey (DHS) program (www.dhsprogram.com), researchers are increasingly utilising methods such as small area estimation and geostatistical additive models to generate high spatial resolution maps of health and development indicators (Blangiardo and Cameletti, 2015; Gething et al., 2015; C. E. Utazi et al., 2018). Such subnational, high-resolution estimates have become useful tools for researchers and policy makers alike in uncovering hidden health inequities which would otherwise be masked by aggregate or national-level health indicators, enabling targeted interventions in settings with limited resources (Pezzulo et al., 2016; C. W. Ruktanonchai et al., 2016, 2018; C. Edson Utazi et al., 2018b; WHO, 2015a).

Visualising health outcomes and associated uncertainty at high spatial resolutions has distinct policy relevance amongst maternal and newborn health (MNH) outcomes (C. Edson Utazi et al., 2018a), as maternal and neonatal mortality both vary geographically and occur relatively rarely. Further, the data associated with maternal mortality are subject to limitations, misclassification, and bias (Ahmed et al., 2014; Ebener et al., 2015), particularly within more rural areas of sub-Saharan Africa where many deaths do not occur at hospitals and may go unrecorded (Say et al., 2014b). As with maternal mortality, data on life-saving MNH interventions such as antenatal care, skilled birth attendance, and delivery via caesarean section (c-section) can be widely obtained at aggregate levels, but remain difficult to measure at subnational levels, especially in the most rural and vulnerable areas of the world. While some work has been done modelling key MNH interventions at subnational scales such as maternal health services, exclusive breastfeeding, childhood vaccinations, and health systems performances, (Bhattacharjee et al., 2019; Mosser et al., 2019; Roberts et al., 2015; C. W. Ruktanonchai et al., 2016, 2018), other vital life-saving interventions which occur less frequently, such as delivery via c-section, have not been modelled previously at high spatial resolutions.

With advancements in computational resources and data availability over recent decades, researchers across disciplines have begun employing Bayesian geostatistical additive models (GAM) to map disease and quantify uncertainty in posterior model outcomes, particularly using hierarchical clustered data such as from the DHS (Blangiardo and Cameletti, 2015; Gething et al., 2015; Magalhães and Clements, 2011; Patil et al., 2011; Schur et al., 2011). The application of these methods is increasingly pertinent, as access to healthcare services is heterogeneously distributed across landscapes, requiring high-resolution spatial data and modelling techniques to identify the most vulnerable populations. However, these methods and associated spatial data carry limitations and bias, manifesting in uncertainty which should be adequately quantified and communicated to decision makers and non-academic audiences for optimum policy impact (Tatem et al., 2012). While the use of such GAMs to predict high-resolution health outcomes has improved model parameter estimates and precision among spatially correlated and rare adverse health outcomes (Gething et al., 2015; Kirby et al., 2017) and allowed for this quantification of uncertainty (Clements et al., 2006b), no studies have examined the trade-off between predicting health outcomes at higher spatial resolutions and visualising the spatial distribution of associated uncertainty (Goovaerts, 2006).

Here, I estimate prevalence of delivery via c-section in Tanzania, using input covariates at varying levels of spatial coarseness within a Bayesian geostatistical model framework. With these models, I investigate how uncertainty varies with spatial resolution, and how this changing uncertainty can be better visualised and communicated. Specifically, I explore the trade-off between model estimates and associated uncertainty at increasing spatial resolutions through exploration of the posterior distribution of modelled delivery via c-section at multiple spatial resolutions.

6.3 Methods

6.3.1 DHS data

I compiled Demographic and Health Survey (DHS) data from Tanzania for 2015 (Ministry of Health et al., 2016) using SAS version 9.4 software (SAS Institute Inc., 2013), and restricted the sample to women with a birth in the preceding 5 years (n = 7,050 women) with corresponding spatial data, as provided by DHS cluster locations. Briefly, the DHS provides GPS coordinates for clusters of aggregated household survey data in order to facilitate spatial analyses, while also maintaining participant confidentiality. These coordinates are displaced up to 2km in urban areas and 5km in rural areas, with up to 1% of points displaced up to 10km in rural areas (Burgert et al., 2013). Using these geo-located cluster locations, spatial inference occurs at a higher spatial resolution than the geographic region in which the survey is designed to be representative of. This hierarchical sample design therefore necessitates the use of geostatistical models to make inferences at spatial resolutions finer than the DHS region level (Gething et al., 2015). In these analyses, the binary outcome of interest was defined as the number of women who underwent any delivery via c-section for a birth within the preceding five years (regardless of whether it was the most recent), as compared to women who had not experienced delivery via c-section for any preceding birth. To maintain survey representativeness, this was calculated at the DHS level 1 resolution, representing the 30 administrative I regions of Tanzania (Figure 6.1).

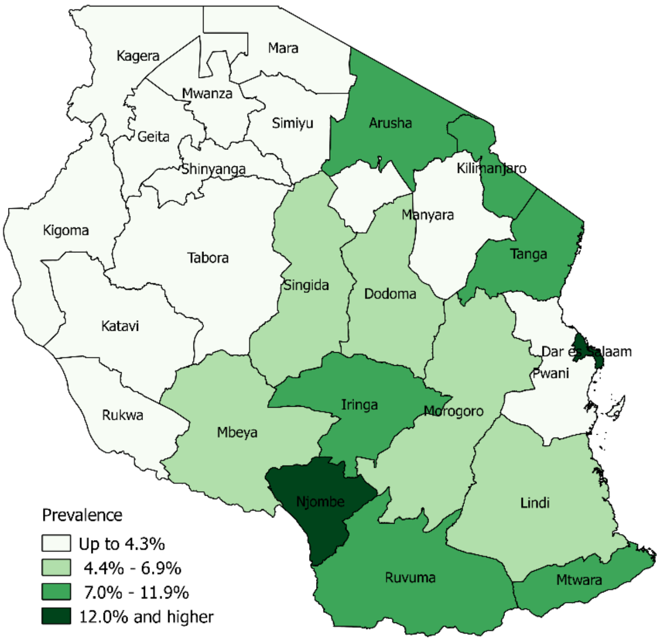

Figure 6.1 Delivery by caesarean section at the administrative 1 level using DHS data, Tanzania, 2015

6.3.2 Covariate data

In addition to demographic data gathered through the DHS, I also compiled environmental geospatial covariate data that I extracted to DHS cluster locations (Figure 6.2). Because these locations are displaced, I averaged geospatial covariates to 2km and 5km buffers for urban and rural locations, respectively. While up to 1% of coordinates in rural areas are displaced within a 10km radius, the addition of buffers at the 10km level have been shown to impact very few rural coordinates (Burgert et al., 2013), while unnecessarily introducing bias in environmental covariates, thereby justifying use of a 5km buffer in rural areas. Firstly, I gathered data from the European Commission’s Joint Research Centre on accessibility to major cities for the year 2000, representing travel time to the nearest city exceeding a population of 50,000 using land (i.e., roads) or water-based travel (i.e., rivers and lakes) (Nelson, 2008). Next, I included data on annual night light intensity for the year 2013 (an indicator of urbanicity), as generated by the National Oceanic and Atmospheric Administration’s (NOAA) National Centers for Environmental Information (NCEI) (US NOAA National Geophysical Data Center and US Air Force Weather Agency, 2014). I also included live births for the year 2015 at the 1 km resolution, as well as Multidimensional Poverty Index (MPI) estimates for the year 2010, as obtained via the WorldPop Project (www.worldpop.org.uk) and outlined by Tatem et al. (A. Tatem et al., 2013; Tatem et al., 2014).

Lastly, I included travel time to the nearest public hospital, as outlined by Ouma et al. (Ouma et al., 2018), calculated through a cost-distance algorithm incorporating a travel impedance surface by assigning travel speed to road networks.

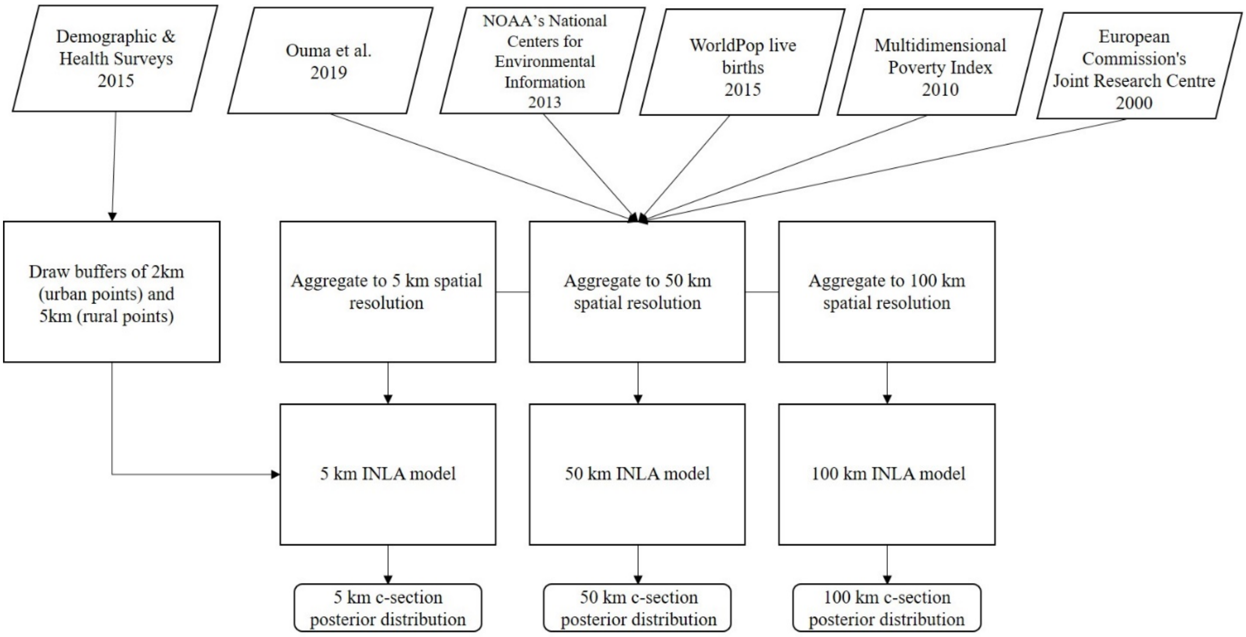

Figure 6.2 Study analysis flowchart

These covariates were chosen as previous studies have shown them to be predictive of MNH outcomes and risks (Bosco et al., 2017; Gabrysch and Campbell, 2009b; Gething et al., 2012; Mpembeni et al., 2007; C. W. Ruktanonchai et al., 2018), representing a suite of geospatial covariates with robust predictive power to examine how uncertainty changes as a function of spatial resolution. Notably, I chose to include only geospatial covariates in this model as I could vary the spatial resolution of these variables, thereby addressing research objectives. Specifically, these datasets were compiled at the 1km spatial resolution, and subsequently averaged at the 5km, 10km, and 100km resolutions to facilitate projecting the fitted model onto gridded surfaces at these levels. These surfaces represent a theoretical exploration of the trade-off between increasing gridded spatial resolution and modelled estimates, and were chosen to clearly illustrate the difference between in the practical range of estimates, as shown in Figure C.8 within Supplementary Information.

6.3.3 Model framework

To explore how uncertainty in posterior modelled c-section delivery estimates varied at multiple spatial resolutions, I employed a Bayesian hierarchical model framework with input covariates at varying spatial coarseness. These models have been used extensively with DHS and other household survey data (Bearak et al., 2018; Hug et al., 2019; Kazembe and Namangale, 2007; Neal et al., 2019; C. Edson Utazi et al., 2018b; C. E. Utazi et al., 2018), as they are able to robustly account for the multi-stage sampling efforts employed during the data collection process, resulting in hierarchically structured data provided through the DHS. Here, these models account for the nested structure of DHS data by allowing for variation in the n^{th} region among individual respondents, as outlined below. These models were fit independently of each other, resulting in 3 models with input covariates and modelled outcomes at the 5km, 50km, and 100km spatial scales. To predict c-section delivery at a continuous spatial resolution, I implemented these models via stochastic partial differential equation (SPDE) spatial regression approach, implemented using the Integrated Nested Laplace Approximation (INLA) technique within the R-INLA package (Rue et al., 2009). This approach was suitable for this analysis as these spatial processes are generally well captured by a Gaussian field with Matérn correlation (Krainski and Castro-camilo, 2018). These models have similarly been used in previous research combining DHS data and geospatial covariates to predict high-resolution childhood vaccination coverage by disaggregating aerial surveillance data (Bosco et al., 2017; C. Edson Utazi et al., 2018b; C. E. Utazi et al., 2018). I employed a similar modelling framework, generally defined as

$$Y_i \sim \text{Binomial}(N_i, p_i), i = 1, \dots, n_A, n_A + 1, n_A + n_p$$

where n_A represents subnational DHS regions within Tanzania to maintain survey representation; Y_i represents the number of women delivering via c-section within area, A_i; p_i represents the probability of a woman delivering via c-section over grid points n_p; and, N_i represent the number of women surveyed within area, A_i.

In this framework, the areal units and observation grid points are linked using the following equations

$$\text{logit}(p_i) = \tilde{x}_i^{'}\beta + |A_i|^{-1} \int n\,(s)\text{d}s + \phi_i, i = 1, \dots, n_A$$

$$\text{logit}(p_i) = x_i^{'}\beta + \eta(s_i) + \phi_{A_i}, i = n_A + 1, \dots, n_A + n_p$$

where x_i and $\tilde{x}_i$ represent covariates for the i^{th} area and grid point, respectively. This framework provides a statistical link between the areal data and high-resolution spatial covariates and random effects, allowing for models at two spatial levels. Further details on the model framework are outlined in Utazi et al. (C. E. Utazi et al., 2018). See (Bosco et al., 2017; Krainski and Castro-camilo, 2018; C. E. Utazi et al., 2018) for more detailed information on similar approaches implementing an SPDE approach of Bayesian hierarchical models via R-INLA using DHS data.

6.3.4 Ethics approval

The University of Southampton Ethics and Research Governance Council Ethics approved this study (ethics approval ID 47073). The data used in these analyses were obtained from the

Demographic and Health Surveys (DHS) Program, which makes global health and demographic data confidentially and freely available to researchers across the world. More information on how the DHS program conducts the Informed Consent process can be found at https://dhsprogram.com.

6.4 Results

Table 6.1 shows posterior marginal effects for the fixed effects within the 5km, 50km, and 100km models as well as model hyperparameters. Fixed effects estimates with upper and lower 95% credible intervals which do not cross 1 are considered significant. Overall, I found that modelled c-section prevalence negatively correlated strongly with poverty and slightly with night-time lights across all spatial scales, as shown in Figure C.7. Of note, night-time lights were not significant within the model, but presented wide credible intervals for marginal effects, as seen in Table 6.1. While poverty was not significant at the 5km scale, it was significant at the 50km and 100km scales, and showed a consistent pattern at the 5km scale with other spatial resolutions (Figure C.7). Conversely, these estimates were strongly positively associated with travel time to the nearest hospital across scales, although this was not significant within the model.

Table 6.1 Marginal effects of the fixed effects and hyperparameters of the posterior c-section models at 5km, 50km, and 100km

Parameter	*5 km*			*50 km*			*100 km*		
	Mean	**Lower 95% CI**	**Upper 95% CI**	**Mean**	**Lower 95% CI**	**Upper 95% CI**	**Mean**	**Lower 95% CI**	**Upper 95% CI**
Accessibility to cities	1.0001	0.9975	1.0027	0.9999	0.9975	1.0022	0.9999	0.9975	1.0022
Night-time lights	0.9603	0.0522	19.7189	0.666	0.0308	14.7623	0.6574	0.0298	14.9301
Live births	1.0471	0.8645	1.2873	0.9915	0.8313	1.1913	0.9938	0.8313	1.197
Poverty	0.0271	0.0005	2.1231	0.0071	0.0001	0.4548	0.0071	0.0001	0.4682
Travel to nearest hospital	1.0046	0.9946	1.0143	1.0062	0.9965	1.0163	1.0063	0.9964	1.0164
Hyperparameters									
	Mean	**SD**	**95% CI**	**Mean**	**SD**	**95% CI**	**Mean**	**SD**	**95% CI**
Θ_1	-0.9259	0.6329	(-2.1791, 0.3104)	0.229	0.942	(-1.636, 2.071)	0.213	0.945	(-1.646, 2.070)
Θ_2	0.1348	0.4988	(-0.8380, 1.1226)	0.041	0.724	(-1.376, 1.472)	0.052	0.718	(-1.352, 1.474)
Precision	1816.2045	1813.6598	(121.78, 6626.24)	5.290	5.794	(0.647, 20.476)	5.814	6.901	(0.648, 23.539)
λ	0.5020	0.2699	(0.0497, 0.9491)	0.354	0.243	(0.031, 0.876)	0.354	0.243	(0.030, 0.876)
DIC	155.67			152.4			152.61		
P_D	17.65			17.70			17.81		
Marginal likelihood	-118.52			-120.84			-120.89		

The large precision estimate for the 5km model as shown in Table 6.1 suggests the spatial process was estimated well with a Gaussian field, while smaller estimates among the 50km and 100km models suggest this was not the case. Regardless, the deviance information criterion (DIC) estimates for the latter two models were slightly improved over the 5km model (Table 6.1). Briefly, these DIC estimates represent a measure of model comparison, trading off between model complexity and model goodness of fit, and performing well among Bayesian models in particular (Spiegelhalter David J. et al., 2002). Smaller DIC values represent models with better fit, given model complexity, suggesting these models perform better as compared to the other models.

Figure 6.3 shows the distributions of the posterior 95% credible intervals for each model as violin plots. These plots show similar summary statistics as boxplots, while also providing information on probability densities, where thinner sections represent a lower probability of a given value occurring. These estimates approximate the trade-off between spatial resolution and uncertainty, representing the density of the width between the posterior upper and lower 95% credible interval for each grid cell for the 5km, 50km, and 100km surfaces. Here, all models had CI widths ranging from near zero to 1, but CI width became more narrowly distributed and approached zero with decreasing spatial resolution. Mean density at the 100km and 50km scales were 0.13 (±0.14) and 0.14 (±0.13), respectively, while mean density at the 5km scale was 0.21 (±0.16).

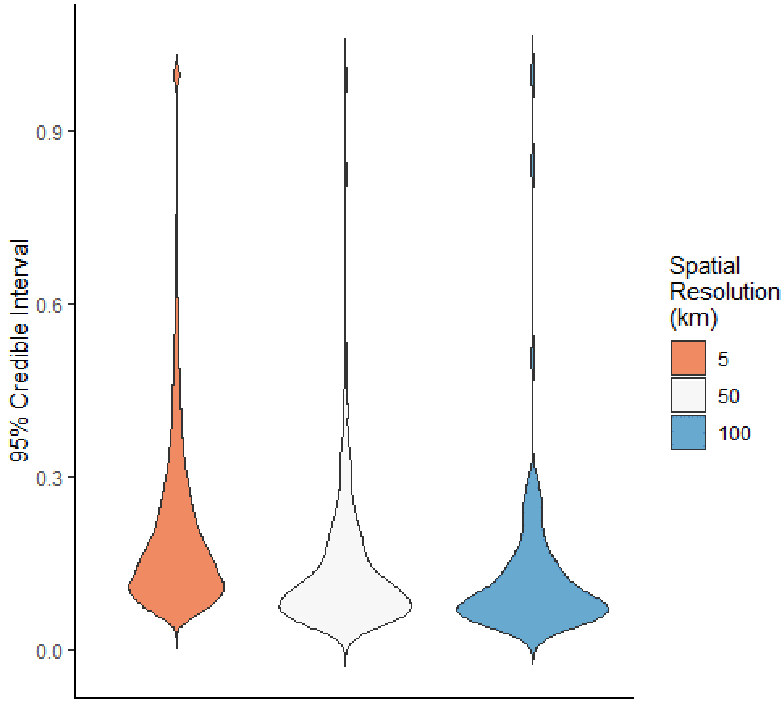

Figure 6.3 Violin plot of posterior 95% credible intervals for c-section estimates predicted at the 5km, 50km, and 100km scale.

Figure 6.4 visualises prevalence of delivery via c-section and associated uncertainty at the 5km, 50km, and 100km spatial resolution. These maps show spatial patterns typical of c-section deliveries, with higher prevalence observed in cities such as Arusha and Dar Es Salaam, and lower prevalence in areas with high inaccessibility to a health facility or amongst more impoverished women (Table 6.1). Overall, the mean estimated prevalence of obtaining a c-section at delivery at the 5km resolution was 8.7% (±6.2%), while the mean uncertainty as measured by the posterior distribution was 20.9% (±15.7%). Mean estimated prevalence was slightly lower at the 50km and 100km resolutions, measuring 7.9% (±4.9%) and 7.8% (±4.8%), respectively, while mean uncertainty was 14.2% (±12.7%) and 13.1% (±14.3%). Areas of higher c-section utilisation were associated with higher uncertainty and observed around major urban areas, notably Dar Es Salaam, Arusha and Moshi, and Dodoma. This trend was observed across spatial resolutions, and in accordance with DHS data. Amongst DHS regions, Dar Es Salaam had the highest prevalence of delivery via c-section at 17%, compared to a national average of 5.9% (Figure 6.1).

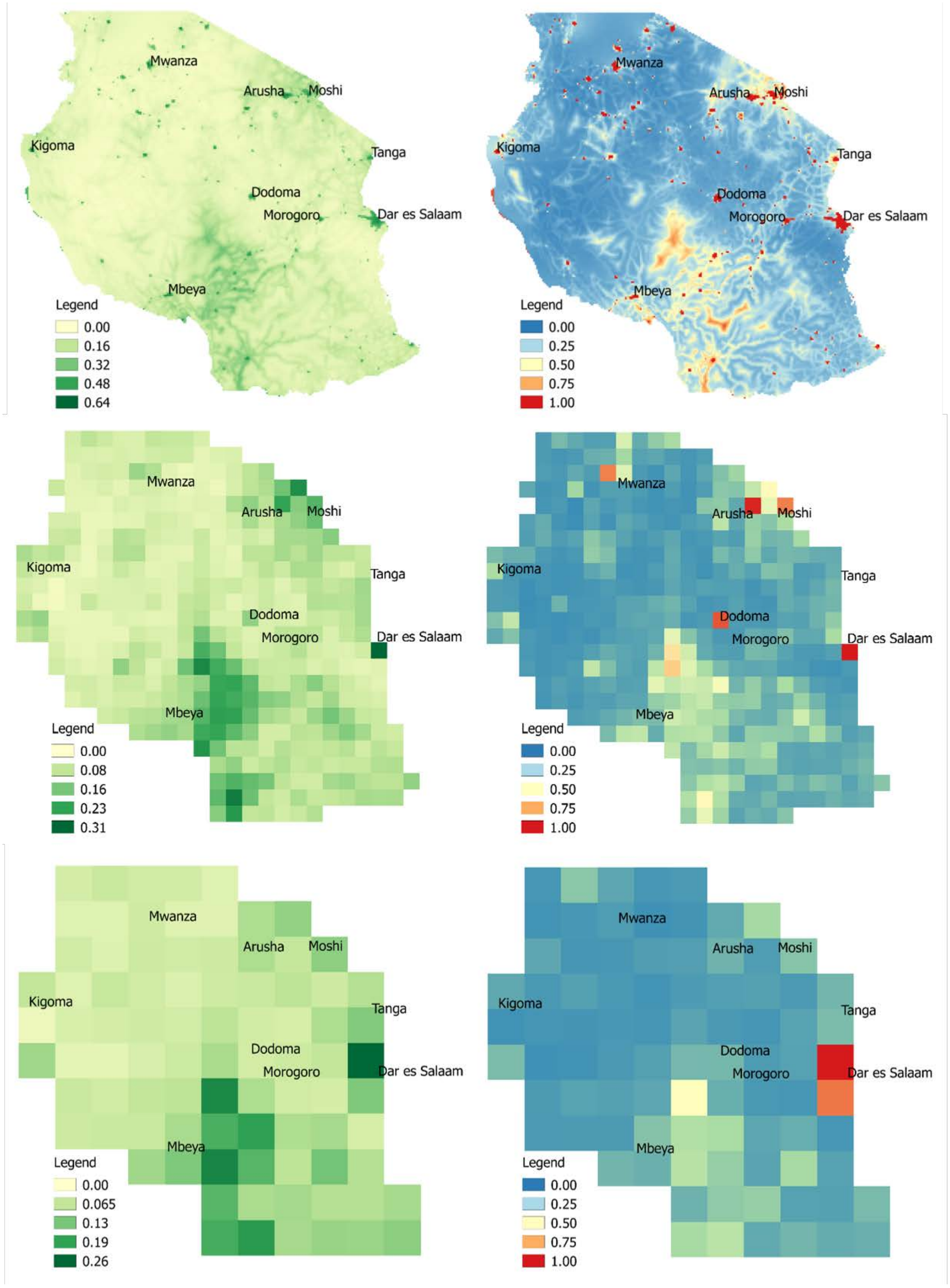

Figure 6.4 Modelled c-section prevalence estimates (left) and associated 95% credible interval (right) at 5km (top), 50km (middle), and 100km (bottom), Tanzania, 2015

6.5 Discussion

Overall, I found increasing model uncertainty associated with increasing spatial resolution, as quantified by increasing 95% credible interval widths (Figure 6.3). This is unsurprising, given that increasing spatial resolution comes with problems of increasingly sparse events, zero inflation, and missing data (Richardson Sylvia et al., 2004). Further, both c-section prevalence as well as model uncertainty tended to be higher in urban areas, reflecting greater variance within the data. This uncertainty could be due to increased data availability within large population centres, or potentially due to GPS displacement error within urban areas. While Bayesian hierarchical modelling techniques have developed to help account for these limitations through rigorous quantification of uncertainty (Gething et al., 2015), these findings suggest an important and often overlooked trade-off persists between modelling these high-resolution health indicators and corresponding policy relevance if these estimates tend to be highly uncertain. Despite increasing uncertainty which accompanied increasing spatial resolution, I found that the 5km model was the most precise, as evidenced by a high precision estimate (Table 6.1). These findings correspond to findings reported in the Tanzania DHS report (Ministry of Health et al., 2016) where rates of c-section utilisation are higher in urban areas. Other studies similarly suggest that while the prevalence of caesarean section is increasing globally (Betrán et al., 2007; Vogel et al., 2015), women in more rural areas that cannot access a health facility quickly have a lower chance of undergoing the procedure in emergency circumstances (Mishra and Ramanathan, 2002; Neuman et al., 2014).

Within the models, I further found that poverty was negatively correlated with undergoing delivery via c-section across spatial resolutions, and was significant at lower spatial resolutions (50km and 100km). These findings are again in line with reported DHS findings suggesting women in the highest wealth quintile were eight times more likely to undergo a c-section as compared to those in the lowest quintile (Ministry of Health et al., 2016). Because health insurance coverage is generally low in Tanzania and relies heavily on payment at point-of-service (Mtei et al., 2012), these findings may suggest that more impoverished women are either unable to afford c-section surgeries when needed, or are generally accessing health care less frequently across the continuum of pregnancy and childbirth.

Researchers are increasingly quantifying health and development indicators at the district level and high spatial resolutions, with aims of achieving Sustainable Development Goals to ensure “no one left behind” (United Nations, 2018; WHO, 2015a). While identifying these previously hidden pockets of vulnerable and marginalised populations is vital to improving the health and well-being of all, the geostatistical methods used to accomplish these goals have inherent uncertainty and bias, which should be communicated effectively to policy makers and other non-academic audiences. While studies have recognized the importance in quantifying this uncertainty (Gething et al., 2015;

Goovaerts, 2006; Richardson Sylvia et al., 2004), no studies have explored how increasing spatial resolution impacts model estimates and uncertainty. This study is therefore the first to map high-resolution estimates of c-section prevalence in Tanzania, and examine the trade-off between increasing spatial resolution and associated model uncertainty in these estimates. These results of this study imply an important trade-off between identifying concealed spatial heterogeneities and accuracy of estimates, which should be optimally communicated in policy relevant settings.

6.5.1 Limitations

This methodological study was exploratory in nature, examining the trade-off between increasing spatial resolution and model uncertainty, and is therefore subject to a variety of limitations. Firstly, I used a suite of standard covariates to explore the impact of spatial resolution alone on model uncertainty, and therefore rigorous covariate selection and model validation efforts were not undertaken during these analyses. As such, the results of these models may not be generalizable to Tanzania, nor to other study countries, and should be used for illustrative purposes only. Further, the spatial resolutions chosen for these analyses represent a theoretical exploration of the impact of increasing resolution on modelled estimates, and are unlikely to represent estimates at resolutions at which policy decisions are made. Future work may explore the impact of increasing spatial resolution on modelled estimates at policy relevant administrative boundaries, as opposed to the rasters employed in these analyses. Secondly, the suite of covariates and DHS data used are subject to their own biases and limitations—for example, the DHS collects data on births within the previous five years, so the estimates presented here may not reflect the current situation within Tanzania. Further, DHS data are not routinely collected registration data, and therefore do not capture information on c-sections performed on women who have subsequently died. This potentially represents biased information, as only women obtaining and surviving the procedure are interviewed. Additionally, travel to the nearest public hospital does not account for individuals who may bypass the nearest facility in favour of a facility with higher quality of care. Lastly, the geospatial covariates used have associated error and misclassification bias, particularly night-time lights which may suffer from light refraction errors, for example. Future work should aim to include more recent data on actual health facility used, where possible, and explore the impact of misclassification bias inherent to these environmental covariates.

6.6 Conclusions

Researchers are increasingly applying Bayesian hierarchical modelling techniques to visualise high-resolution spatial patterns of health indicators. These techniques offer powerful and rigorous methods to quantify and visualise model uncertainty, but few studies have explored how to communicate this uncertainty in policy-relevant settings. Here, I explored how model uncertainty changes with increasing spatial resolution, and found that while uncertainty increases with higher spatial resolutions, model precision was best approximated at the highest spatial resolution, suggesting an important policy trade-off between identifying concealed spatial heterogeneities in health indicators. In modelling delivery via c-section at multiple spatial resolutions, I demonstrate poverty to be negatively correlated across spatial resolutions, suggesting important disparities in obtaining life-saving obstetric surgery persist across sociodemographic factors. This work is the first study to explore modelled c-section estimates and uncertainty at varying spatial resolutions, and has potential policy implications in terms of visualising spatial patterns of obstetric surgery, as well as focusing maternal and newborn health data collection efforts within Tanzania.

6.7 Acknowledgments

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6.8 Intellectual contribution

The author list for this published work is as follows: Ruktanonchai CW, Nieves JJ, Ruktanonchai NW, Nilsen K, Steele JE, Matthews Z, Tatem AJ. CWR conceived of the study framework and methods for this study, performed all data management and analysis, generated all study visualizations and results interpretations, and wrote and prepared the manuscript for journal submission. JJN and NWR contributed insight and feedback on the conceptual study design, as well as statistical feedback on analysis and model results. KN and JES provided input on how the study results fit into the broader fields of maternal health and geography, respectively. Lastly, ZM and AJT supervised CWR during production of this manuscript, and oversaw that methods and analysis were executed within a sound and scientifically rigorous framework. All authors reviewed the manuscript and provided feedback before final submission to the journal.

Chapter 7: Conclusions

To ensure 'no one left behind' in improving the health of the most vulnerable women and children, the disaggregation of MNH outcomes at high spatial resolutions will be crucial over the coming decades (Molla et al., 2019). Despite this, the use of spatial statistics and geospatial methods in MNH research remains limited (Ebener et al., 2015). This thesis aimed to broadly address this knowledge gap by: 1) producing methods to estimate utilisation of key MNH services, highlighting high spatial resolution and policy-relevant inequalities; 2) tracking how these spatial inequalities in utilisation of MNH services have changed over time, identifying sub-national regions which have made progress in narrowing inequalities over time, as well as regions where progress still needs to be made; and, 3) exploring the trade-off between increasing spatial resolution of modelled estimates and associated uncertainty in model outcomes. In this section, I discuss the key findings of this work, followed by contributions this work has made to academic literature, as well as limitations of these analyses and future work. Lastly, I outline the policy and development implications of this work, followed by concluding remarks.

7.1 Key findings

Table 7.1 outlines a synthesis of key research findings of this thesis, by overall study objective and subsequent research question addressed in each analysis. As each study objective was addressed by a single paper, these are designated as 'Paper 1', 'Paper 2', and 'Paper 3'. Table 7.1 further outlines the key gaps in knowledge related to each study objective, as well as the data and methods used in each analysis. Addressing Study Objective 1 in Paper 1 (Chapter 4), I found that lower wealth and education levels within the East Africa region were associated with less odds of obtaining MNH care, while higher geographic inaccessibility scores were associated with the strongest effect in lowering odds of obtaining different types of care, with the widest disparities seen for skilled birth attendance. Kenya and Tanzania showed generally lower probabilities of obtaining key MNH services, while Rwanda and Burundi had generally higher odds of women utilising these services, possibly due to relatively higher density of health facilities.

Addressing Study Objective 2 in Paper 2 (Chapter 5), Rwanda represented the only country to increase coverage over time amongst all MNH services examined, with as much as 85% increases in SBA for some districts and nearing universal coverage for both SBA and PNC. Conversely, Tanzania experienced noticeable reductions in coverage throughout most of the country in utilisation of ANC, with some areas seeing as much as a 55% reduction, driven in part by exceedingly high estimates in earlier survey years. Across all countries, the relative gap in coverage within countries tended to be the most equitable for ANC coverage, while SBA and PNC tended to have greater gaps between the highest and lowest district estimates within countries, suggesting greater spatial disparities. Over time, however, the region has generally made progress in reducing spatial disparities within countries, yet improvement in PNC coverage has stagnated, and must continue to be monitored over the coming decades.

Addressing Study Objective 3 in Paper 3 (Chapter 6), increasing model uncertainty was generally associated with increasing spatial resolution, as quantified by increasing 95% credible interval widths. Despite this, the model showing the greatest precision was the model with the highest spatial resolution at 5km. Further, both c-section prevalence as well as model uncertainty tended to be higher in urban areas, potentially reflecting greater variance within the data, most likely due to more data availability within large population centres. These findings suggest an important and often overlooked trade-off persists between modelling these high-resolution health indicators and corresponding policy relevance if these estimates tend to be highly uncertain. Lastly, these methods can be applied to other regions throughout the world, and represent an integration between geolocated survey data and geospatial covariates that can reliably map MNH coverage at high spatial resolutions and across time. By applying these methods, researchers and policy makers can track spatial inequalities in key health coverage indicators throughout the SDG timeframe.

Table 7.1 Key research findings, by study objective

Study objectives	Research questions	Gaps in knowledge	Data & methods	Key findings
Paper 1: Produce high-resolution and policy relevant probabilities of utilisation of MNH services as predicted by geographic accessibility, highlighting spatial heterogeneity and sub-national inequalities	1) What are the primary drivers of utilisation of antenatal care, skilled birth attendance, and postnatal care within the East African Community study region? • Does geographic accessibility to a health facility predict utilisation of these services, and does this vary by service utilised (i.e., ANC, SBA, versus PNC)? 2) Provided current health facility locations throughout the study region, where are women most likely to utilise these MNH services at both a high-resolution (300 x 300 m) scale and policy-relevant scale (administrative level II)?	• Use of spatial statistics to identify previously hidden health inequalities is key to ensuring 'no-one left behind' in SDG era (WHO, 2015a) • Spatial analysis of MNH outcomes remains limited (Ebener et al., 2015; Molla et al., 2019, 2017) • No previous studies have explored geographic accessibility as a determinant across the spectrum of pregnancy at a high spatial resolution	• Hierarchical mixed effects model to estimate odds of: 4+ antenatal care visits (ANC), skilled birth attendance (SBA), postnatal check-up within 48 hours (PNC) • Fixed model effects included: urban/rural residence; education status; wealth quintile; maternal age; parity, and interaction term between age and parity • Primary explanatory variable: Geographic accessibility to nearest health facility • Most recent DHS data used, N = 25,325 women with birth in preceding 5 years • 9,314 facilities used to create geographic accessibility surface (primary explanatory variable)	• Across all outcomes, decreasing wealth and education levels were associated with lower odds of obtaining MNH care • Increasing geographic inaccessibility scores were associated with the lowest odds of obtaining care observed across outcomes, with the widest disparities observed among skilled birth attendance • Kenya and Tanzania had generally lower probabilities of obtaining all MNH services, with the lowest probabilities observed throughout rural districts in northern Kenya and central Tanzania • Conversely, Rwanda and Burundi had generally higher probabilities of obtaining care, possibly due to increased facility density • Higher probabilities of obtaining care were observed in urban versus rural districts, further indicating infrastructure density is important factor in predicting MNH care utilisation • The integration of geo-located survey data with geospatial covariates in statistical models can reliably map coverage of MNH service utilisation at fine spatial scales

Study objectives	Research questions	Gaps in knowledge	Data & methods	Key findings
Paper 2: Track how spatial inequalities in utilisation of MNH services have changed over time, identifying sub-national regions which have made progress in narrowing inequalities over time, as well as regions where progress still needs to be made	3. How has coverage in SBA, ANC, and PNC within study countries changed absolutely over time, by administrative unit II? • Which administrative units have had the most improvement in coverage? Which have had the least improvement? 4. How does the change in coverage among these administrative units compare relative to each other? a. How wide is the change-in-coverage gap between administrative units within a country? b. Has this change-in-coverage gap improved over time, gotten worse, or stayed the same?	• Spatial inequalities in access to life-saving MNH services persist within sub-Saharan Africa • Previous studies have systematically reported child and maternal mortality at the global, regional, and national level (Alkema et al., 2016b; Black et al., 2010), and health indicators such child growth (Osgood-Zimmerman et al., 2018) at high spatial resolutions, but fewer studies have examined temporal trends in utilisation of key MNH services at similar spatial resolutions • While Paper 1 examined utilisation of MNH services as an emergent property of accessibility at high spatial resolutions, no research has examined how these spatial inequalities have evolved over time at similar spatial scales	• Compiled data from DHS for Kenya, Tanzania, Rwanda, and Uganda for several time points available (see Table 5.1) • Employed a Bayesian model framework using the Integrated Nested Laplace Approximation (INLA) package in R software to spatially interpolate coverage estimates for ANC, SBA, and PNC at the district level • Fixed model effects included: urban/rural residence; education status; wealth quintile; maternal age; parity • Absolute inequality: compared estimates for each country between the first and last surveys available • Relative inequality: quantified the ratio between best-versus-worst modelled estimates among districts	• Rwanda represented the only country with exclusively increasing coverage over time amongst all three services, with as much as 85% increases in SBA for some districts and nearing universal coverage for both SBA and PNC • Conversely, Tanzania had noticeable reductions in coverage throughout most of the country in utilisation of ANC, with some areas experiencing as much as a 55% reduction • Across all countries, the relative gap between countries tended to be smallest among ANC (with the exception of Rwanda), while SBA and PNC tended to have greater gaps between the highest and lowest district estimates, suggesting greater spatial heterogeneity • Historically, Rwanda had relatively small ratios which decreased over time, while Kenya had the highest inequalities in SBA, these were substantially reduced over time • While the region is generally making progress in reducing spatial gaps across districts, improvement in PNC coverage has stagnated • These methods can be applied over time to monitor progress in reducing absolute and relative inequalities in MNH service utilisation

Study objectives	Research questions	Gaps in knowledge	Data & methods	Key findings
Paper 3: Explore the trade-off between increasing spatial resolution of modelled estimates of delivery via caesarean section in Tanzania, and associated uncertainty in model outcomes	1) What is the trade-off between increasing spatial resolution and model fit? • How does the overall posterior distribution of the 95% credible interval change with increasing spatial resolution? 2) How does uncertainty in estimates of prevalence of delivery via c-section propagate spatially across the landscape at varying resolution sizes? • Are there areas with consistently high or low estimates of delivery via c-section across spatial resolutions? • Are there areas with consistently high or low uncertainty across spatial resolutions?	• Advancements in computational resources and data availability have allowed researchers across disciplines to employ Bayesian geostatistical additive models (GAM) to map disease and quantify uncertainty in posterior model outcomes, particularly using hierarchical clustered data such as from the DHS (Blangiardo and Cameletti, 2015; Gething et al., 2015; Magalhães and Clements, 2011; Patil et al., 2011; Schur et al., 2011) • GAMs have improved model parameter estimates and precision among spatially correlated and rare adverse health outcomes (Gething et al., 2015; Kirby et al., 2017) • No studies have explored how increasing spatial resolution impacts model estimates and uncertainty (Goovaerts, 2006)	• DHS data for Tanzania, 2015, N = 7,050 women with birth in preceding 5 years • Employed a Bayesian hierarchical model framework with input covariates at the 5km, 50km, and 100km spatial scales • Implemented via stochastic partial differential equation (SPDE) spatial regression approach, using the Integrated Nested Laplace Approximation (INLA) technique • Binary outcome of interest: woman underwent any delivery via c-section for a birth within the preceding five years • Environmental covariates: accessibility to major cities, night-time lights, live births, Multidimensional Poverty Index estimates, and travel time to nearest hospital	• Overall, increasing model uncertainty was associated with increasing spatial resolution, as quantified by increasing 95% credible interval widths • Despite increasing uncertainty which accompanied increasing spatial resolution, 5km model had greatest model precision • Findings suggest an important and often overlooked trade-off persists between modelling these high-resolution health indicators and corresponding policy relevance if these estimates tend to be highly uncertain • Both c-section prevalence as well as model uncertainty tended to be higher in urban areas, reflecting greater variance within the data, most likely due to more data availability within large population centres

7.2 Thesis contributions

This work explores the spatial inequalities in accessibility to key MNH services in the East Africa region, how these inequalities have evolved over time, and the trade-off between modelled estimates at high spatial resolutions and model uncertainty. In doing so, this work makes several novel contributions to the scientific literature.

The analyses comprising Chapter 4 represented the first of their kind to model the probability of obtaining antenatal care, skilled birth attendance, and postnatal care at high spatial resolutions in the East African region. Further, while previous studies have examined geographic accessibility to health facilities in the context of obtaining emergency care, no studies have reported the probability of obtaining routine MNH services, as predicted by geography. There has consequently been a call for using geospatial analysis and GIS tools to explicitly account for the effect of geographic variation in key MNH outcomes and service utilisation (Makanga et al., 2016). These analyses were therefore also the first study to model these outcomes as an emergent property of geographic accessibility using a geo-located database of nearly 10,000 health facilities throughout the region. Lastly, the geo-located database assembled for this study also represented the first of its kind to be openly available to researchers with detailed information on location, operational status, public/private ownership, and facility type. These results demonstrate how novel spatial approaches can be utilised to inform policy efforts and promote evidence-based decision-making, making substantial contributions to both the academic literature in addition to policy contributions.

While the analyses outlined in Chapter 4 examined spatial inequalities in MNH service utilisation, no research has similarly looked at how these spatial inequalities have evolved over time, particularly at high spatial resolutions. Previous research has examined inequalities in key MNH outcomes, including ANC, SBA, and PNC, disaggregated by socio-economic factors such as wealth quintile and education (WHO, 2015a) and geographical factors such as DHS region (Assaf and Pullum, 2016). However, no research has disaggregated these inequalities over time at policy-relevant, high spatial resolutions such as the administrative level II unit. The analyses comprising Chapter 5 therefore represent the first to report temporal trends in spatial inequalities among these services within the region at policy-relevant scales, particularly in the context of both absolute and relative health inequalities. Further, while previous work has reported temporal trends in inequalities as measured by logit regression coefficients such as wealth quintile (Assaf and Pullum, 2016), these analyses were the first to report logit regression coefficients of the effect of DHS region, representing temporal trends in spatial inequalities, divorced of modelled estimates. By reporting trends in district-level MNH service utilisation throughout these study countries, this work contributed to the academic literature, and further established a baseline of evidence moving forward into the Sustainable Development Goal era.

Lastly, while the use of Bayesian geostatistical approaches have allowed for the estimation of MNH service utilisation at high spatial resolutions, no previous research has examined the optimal spatial resolution to model outcomes or the trade-off between increasing spatial resolution in model inputs and resulting model uncertainty. The analyses comprising Chapter 6 of this work were the first to report on model uncertainty resulting from increasing spatial resolution inputs. The results of this work suggest an important trade-off between identifying concealed spatial heterogeneities and accuracy of estimates, which should be communicated in policy relevant settings.

7.3 Limitations

The analyses comprising this work are broadly subject to limitations, as outlined within each corresponding chapter. Notably, DHS data were used throughout all analyses in this work, and are subject to a variety of limitations. Firstly, statistical inference was made at administrative units smaller than the geographical units at which these data are representative, potentially resulting in model uncertainty and sampling error. However, the DHS has provided guidance on how to perform such inference in a robust and statistically valid way (Gething et al., 2015), endorsing the use of Bayesian geostatistical methods which can quantify the resulting uncertainty. Secondly, women with births in the preceding five years were used throughout these analyses, potentially representing a time lag between data collection and analysis. Therefore, these analyses may not represent the current state of MNH service utilisation, instead representing trends up to five years previous. As these limitations are inherent to DHS data, they potentially impact results reported throughout all three analyses.

In addition to the above broad limitations, each analysis is also subject to its own limitations specific to the methods used. Firstly, within the analyses comprising Chapter 4, some health facilities were not included in the geographic accessibility analysis. These facilities were excluded as they were deemed unlikely to offer maternal and newborn health services, but it is possible that some facilities did indeed offer services and were therefore inaccurately excluded. In this scenario, geographic accessibility would be inaccurately decreased for some participants, introducing error into model results. Further, I assumed accessibility to the nearest health facility in these analyses, which is very often not the reality of the situation, as many women bypass the nearest health facility in lieu of facilities offering higher quality of care or as a result of an emergency referral (De Allegri et al., 2011; Hulton et al., 2016). While actual health facility used would be the ideal input into these geographic accessibility analyses, these data were not available for these study countries. Secondly, the outcomes used in this analysis varied by country, specifically in regards to skilled birth attendance. While women were asked to recall whether a skilled attendant was present at delivery, it is possible women were not aware of the qualifications of their attendant, potentially introducing recall bias into these analyses. Further, even though these analyses use the WHO definition of skilled birth attendance as trained ‘doctors, nurses, and midwives’, qualifications and titles may vary between countries, further resulting in error (Adegoke et al., 2011).

Within the analyses comprising Chapter 5, the time lag inherent to DHS data may have a particular impact on temporal trend analyses. Further, while the most recent DHS data were used in these study countries, many countries did not have data available for the past 5 years, and indeed Burundi had only one time point available and could therefore not be included in these analyses. More recent data representing births within a timelier window is necessary to confirm the trends reported. Lastly, similar to Chapter 4, actual health facility used was not used in these analyses, as these data were not available. In cases where women may be referred to a district hospital or may travel long distances to give birth elsewhere (such as when staying with family, etc.), error is potentially introduced into the models, as where MNH services were utilised does not necessarily reflect the district where the respondent was surveyed at the time of data collection.

Lastly, the suite of covariates used in the analyses comprising Chapter 6 were not rigorously tested as predictors of delivery via c-section, as the scope of the study was to explore the trade-off between increasing spatial resolution and model uncertainty. While these covariates have been used in previous studies, it is possible they do not predict delivery via c-section rigorously, and any model results should therefore be interpreted cautiously, as results may not be generalizable to the rest of the study region because model validation efforts were not undertaken. Further, the spatial resolutions chosen for these analyses represent a theoretical exploration of the impact of increasing resolution on modelled estimates, and are unlikely to represent estimates at resolutions at which policy decisions are made. Future work may explore the impact of increasing spatial resolution on modelled estimates at policy relevant administrative boundaries, as opposed to the rasters employed in these analyses. Secondly, similar to previous chapters, time to health facility represented time to the nearest health facility, potentially overlooking scenarios in which a woman bypasses the nearest health facility due to referral, higher quality of care, etc. Additionally, travel estimates are also subject to bias themselves, as mobility patterns vary by season, and information on road quality is not captured, excluding smaller footpaths which may be used in transit. Lastly, other environmental covariates such as night-time lights have associated misclassification bias due to light refraction, etc., potentially introducing further error into the models.

7.4 Future work

Future work should address the broad limitations inherent to these studies, as outlined above, with aims of strengthening data quality and analysis. Firstly, future work should include information on actual health facility used where possible, and examine how this compares to assumptions made regarding nearest health facility. Along these lines, mobility data reflecting actual movement patterns among pregnant women should be used, as collected by mobile phone technology, for example. Previous work suggests that women living in high poverty, rural areas may be historically under-represented in mHealth program interventions that utilize mobile phone ownership to target and access hard to reach, remote populations (Wesolowski et al., 2012). While some work has explored mobility patterns among more broad populations using mobile phone technology such as call data records (CDRs), this work tends to employ anonymized datasets for security and privacy reasons (González et al., 2008; Lai et al., 2019). More recently, Google Location History (GLH) data has been explored as a potential novel source to link mobile phone usage patterns and data on sociodemographic and health surveys (N. W. Ruktanonchai et al., 2018), but no work has explored mobility patterns among pregnant women specifically, particularly within the context of health facility accessibility. Future work should therefore aim to collect individual level health and demographic data on pregnant or recently pregnant women, in combination with actual mobility patterns to health facilities used throughout the spectrum of pregnancy.

Secondly, while nationally representative surveys such as DHS and MICS surveys offer researchers an opportunity to follow health over time, these data are collected infrequently every 3 to 5 years and are therefore subject to time lag, decreasing their suitability for SDG monitoring. Data collection efforts can be further hampered by political instability and conflict, as evidenced by a lack of DHS data in Burundi, preventing its inclusion in analyses performed in Chapter 5. Lastly, these surveys frequently evolve over time, potentially limiting their comparison over time, as well. To overcome these issues, routine health management information systems (HMIS) and national registry data regularly collected by ministry of health programmes offer a potential way forward.

A highly functioning HMIS will collect information on health systems resources, such as personnel, financing, and infrastructure, that can then be used to measure progress in key health indicators, compile a variety of data sources including census data and nationally representative survey data, manage data to aggregate forms such as health catchments and administrative units, and disseminate data products to key stakeholders (Health Metrics Network, 2008). While many countries struggle to compile a functional HMIS due to competing priorities and limited resources, other countries such as Kenya, Sierra Leone, South Africa, Malawi, and Zanzibar have successfully integrated their HMIS into an online, open-source platform such as the DHIS2.

The aim of DHIS2 implementation is ultimately to "generate, analyse, and disseminate health information to facilitate effective policy formulation, management, planning, budgeting, implementation, monitoring and evaluation of health services and program interventions in the health sector" (Karuri et al., 2014). Ideally, this system should be implemented with local and national support, and include a collaborative network of scientists and researchers who can disseminate analysis to stakeholders appropriately. Further, to ensure successful consolidation of routinely collected health data, quality and standardization of data must occur, as evidenced by successful implementation in Sierra Leone and South Africa (Karuri et al., 2014). Without ensuring data quality, researchers are often left to utilise surrogate methods to account for missing and unreliable data, such as aggregating to operational administrative units and utilising Bayesian inference (Alegana et al., 2016). As the world continues to move closer a 2030 deadline, it is vital that future efforts ensure that otherwise fragmented surveillance data and irregularly collected survey data are consolidated and standardized into similar DHIS2 platforms, allowing for monitoring and evaluation of key SDG indicators over time.

Lastly, future work should prioritise surveillance and geo-coding of maternal deaths and strengthening mortality statistics. In order to strengthen these systems, maternal deaths occurring outside of health care centres and hospitals must be recorded, geographic coordinates must be collected, and data must be checked to ensure quality control. These data should be captured by routine health systems data, and available to ministries of health and technical experts, as discussed above. Once these data are available, routine visualisation and monitoring and surveillance efforts can occur to better understand where inequalities in maternal deaths persist, helping to focus interventions. Until countries are able to visualise where maternal deaths are occurring, policy makers are left to best estimate where resources and intervention efforts are best applied.

7.5 Policy and development implications

The analyses comprising this thesis have several policy and development implications, as evidenced by its inclusion in region-specific policy briefs. Ensuring that SDG targets are met by the year 2030 necessitates ensuring that the hidden pockets of the most vulnerable women and children are identified and addressed. Towards this, no single intervention is sufficient in preventing unnecessary deaths and ill health among these populations, but instead universal health coverage and access to high quality of care is essential over the coming years. However, in the absence of universal health coverage indices, key intervention indicators will be crucial in monitoring health coverage and resulting inequalities (World Health Organization and International Bank for Reconstruction and Development/The World Bank, 2017). It is therefore crucial that researchers and governments monitor the change in coverage over time in these indicators at sub-national levels to ensure that progress is made not just at national levels, which can hide important disparities within countries, but good health is achieved amongst all women and children, leaving no one behind.

These analyses demonstrate how spatial approaches can be used to inform monitoring and evaluation efforts and promote evidence-based policy making decisions. These applications, however, must be adopted and maintained by experts within the region in order to ensure analyses are relevant and sustainable over the course of decades (Tanser and le Sueur, 2002). It is therefore crucial to ensure ongoing capacity strengthening and knowledge exchange efforts are maintained. Towards this, the analyses comprising Chapter 4 of this work were informed by key interventions monitored by the intergovernmental East Africa Community’s RMNCAH Scorecard Framework, a tool for tracking and communicating progress in key RMNCAH interventions to key stakeholders in the region. More importantly, the results of these analyses were communicated back to collaborators through in-country workshops, such as *The Workshop and Technical Exchange on the use of advanced Geographic Information System (GIS) enabled mapping and validation of the 2nd annual EAC RMNCAH Scorecard*, which I hosted in 2016. By building and maintaining these collaborative networks and capacity strengthening efforts, the spatial approaches outlined in this body of work may be sustained within country by local experts with the appropriate technical and cultural knowledge to monitor and evaluate progress. This is further evidenced within the region-specific policy brief, *The State of the World's Midwifery: Analysis of the Sexual, Reproductive, Maternal, Newborn and Adolescent Health Workforce in East & Southern Africa*. Here, these analyses demonstrated the utility of GIS tools in highlighting sub-national inequalities for use in decision making. By collaborating with policy makers at EAC throughout the entirety of this work, strong collaborative networks were built, facilitating and complementing ongoing in-country efforts to monitor and strengthen reproductive, maternal, newborn, adolescent, and child health efforts.

The results of these analyses have further policy implications that should be communicated back to stakeholders and decision makers within the region. The results of Chapter 4 suggest that allocating funds for increased infrastructure such as health facilities, health workforce, and road networks, as well as upgrading existing infrastructure, may help in alleviating some of the inequalities observed within the region. Specifically, funds can be allocated towards efforts to improve geographic accessibility to health facilities, such as paving road networks, increasing transportation services, and building bridges in areas likely to flood in the rainy season. However, increasing accessibility alone is insufficient in increasing service utilisation, particularly among services such as skilled birth attendance where unplanned emergencies may increase barriers to utilising these services. Ultimately, investing in infrastructure such as increased density and higher quality of health facilities and health workforce will be crucial in reducing adverse MNH outcomes amongst resource-poor settings. By highlighting sub-national and high spatial resolution inequalities within the region, policy makers can better allocate resources and funds to areas of the region most at-risk of low service utilisation, ultimately ensuring no gaps in health coverage across the continuum of pregnancy and delivery.

The analyses comprising Chapter 5 of this work aimed to monitor the progress of coverage of these services over time, highlighting areas within the region where progress in increasing coverage was being made, as well as areas where work was still needed. This represented the first study to examine change in spatial inequalities over time at these spatial resolutions, where previous studies have used aggregate outcomes masking underlying spatial variance. Basing policy on such aggregations is problematic, is not resource efficient, and misses those most in need. The results of these analyses therefore have important policy implications, and suggest that progress in reducing disparities in service utilisation has varied across the region, with some countries performing better than others in reducing coverage gaps.

In particular, Rwanda has made exceptional progress in ensuring high universal coverage across all MNH services studied, as well as ensuring progress is made across the country in a spatially equitable manner. Further, as the only country within the region to achieve MDG targets of reducing maternal mortality by 75% between 1990 and 2015, the country represents a potential case study in how to prioritize and improve maternal and child health. Specifically, Rwanda has radically redeveloped their health system, aiming to implement tiered national health insurance schemes available to even residents unable to afford insurance, performance-based pay schemes to incentivize high quality health workforce, and coordination between government aid and external donors (Logie et al., 2008). While these policies may not be suitable for other countries within the region, they demonstrate a commitment to improving RMNCAH over the previous decades, suggesting that aggressive investment in women and children's health and human rights at the national level is necessary to reducing preventable deaths and adverse health outcomes.

Lastly, the analyses comprising Chapter 6 of this study suggest caution in interpreting results without fully comprehending the associated uncertainty in model estimates. While estimates of MNH service utilisation and health outcomes is increasingly necessary in identifying hidden spatial inequalities, the results of this chapter suggest uncertainty also increases with increasing spatial resolution. This represents an important trade-off between increasing spatial resolution and accuracy of model estimates, suggesting that researchers and policy makers should collaborate on the optimal geographical unit to predict health outcomes and service utilisation. This further has important policy implications in the context of communicating uncertainty to policy makers, which is not an intuitive or approachable task, even amongst researchers. While the ultimate decision of how, when and where to allocate resources and funds lies with policy makers, researchers have a responsibility to communicate the limitations of such analyses to these decision makers, else limited resources are at risk of being inappropriately and inefficiently distributed.

The collective results comprising this work suggest that collaboration and buy-in among policy makers is crucial to ensuring the appropriate research questions are addressed and results are interpreted in a culturally competent way. It is not the role nor right of the researcher to make distinct policy recommendations, particularly among countries where the researcher lacks context. Instead, policy makers and key stakeholders should be consulted throughout all phases of the research development, from inception to study objectives to funding to interpretation and dissemination. Without the participation and engagement of the representatives most affected by these health challenges, research will continue to be isolated, unsustainable, and patronizing. Examples of knowledge exchange activities could include capacity strengthening workshops aimed at increasing technical knowledge, participatory focus groups between researchers and key stakeholders, joint funding endeavours shared between researchers and policy institutions, and increased coordination and communication amongst in-country health sectors and academic institutions.

7.6 Conclusions

Progress in maternal and newborn health (MNH) outcomes has historically been monitored at aggregate levels such as the global, regional and national level, yet these measures show vast inequalities sub-nationally. While previous work has disaggregated MNH outcomes by socio-economic factor such as wealth, quintile, place of residence, etc., (Assaf and Pullum, 2016; WHO, 2015a) less work has aimed to visualise MNH outcomes and service utilisation at high spatial resolutions and policy-relevant scales such as the district level, particularly within a framework explicitly accounting for geographic variation. This work utilised geospatial approaches such as cost-distance analysis, mixed effects hierarchical modelling, and Bayesian geostatistical models to visualise disparities in key MNH services throughout the East Africa region at multiple spatial resolutions. Further, this work examined how these spatial disparities have evolved over time within these countries, using both absolute and relative inequality indices, with aims of highlighting where improvement has been made in closing the gaps in these spatial disparities, and where progress still needs to be made. Lastly, this work examined the trade-off between reported model outcomes at increasing spatial resolutions and associated model uncertainty. The analyses contained in this thesis have been published in rigorous academic journals, as well as featured in regional policy briefs, making substantial contributions to the academic literature and policy spheres. The findings contained in this work demonstrate the utility of spatial approaches in identifying previously hidden MNH inequalities, which can inform and direct policy efforts and evidence-based decision-making. These approaches will become increasingly critical in the post-2015 Sustainable Development Goal era, where new approaches in identifying and reducing persistent inequalities will be key to ensure no one is left behind.

Appendices

Appendix A Chapter 4 Appendix

A.1 Chapter 4 Supplementary Figures

Figure A.1 Geo-located DHS clusters (N = 3,311) by number of DHS respondents (N = 36,178) and urban versus rural location in five East African countries.

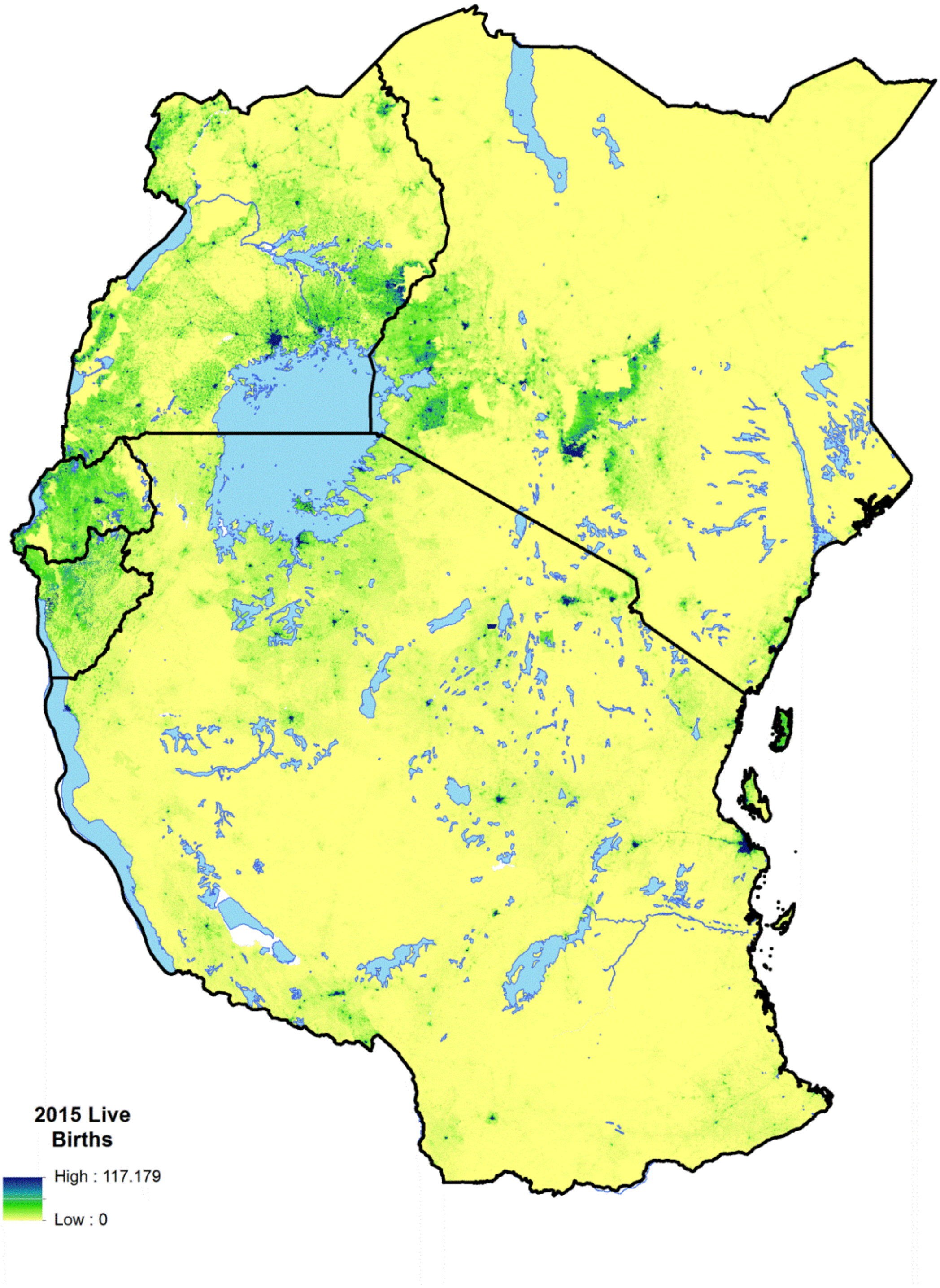


Figure A.2 Estimated live births in five East African countries. Birth estimates were generated by the WorldPop project (www.worldpop.org) and are shown for the year 2015 at 100 x 100 m resolution.

Appendix B Chapter 5 Appendix

B.1 Chapter 5 Supplementary Tables

Table B.2 Unadjusted logistic regression results, with worst performing DHS region as reference, as compared to best performing DHS region.

Outcome	Year	Worst performing Region (Reference)	Best performing region (Coefficient)	Model coefficient (±SD)
Kenya				
SBA	2003	North Eastern	Nairobi	3.33 (0.22)
ANC		North Eastern	Nairobi	2.80 (0.21)
PNC		North Eastern	Nairobi	3.38 (0.23)
SBA	2008	Western	Nairobi	2.65 (0.19)
ANC		North Eastern	Nairobi	1.78 (0.18)
PNC		North Eastern	Nairobi	2.34 (0.29)
SBA	2014	North Eastern	Nairobi	2.76 (0.18)
ANC		North Eastern	Nairobi	1.55 (0.13)
PNC		North Eastern	Central	1.77 (0.32)
Outcome	**Year**	**Worst performing Region (Reference)**	**Best performing region**	**Model coefficient (±SD)**
Tanzania				
SBA	1999	Kigoma	Dar Es Salaam	2.37 (0.49)
ANC		Kigoma	Dar Es Salaam	3.22 (0.6)
PNC		Kigoma	Dar Es Salaam	1.27 (0.5)
SBA	2010	Pemba North	Dar Es Salaam	2.82 (0.27)
ANC		Pemba North	Dar Es Salaam	2.09 (0.23)
PNC		Mwanza	Ruvuma	1.05 (0.51)
SBA	2015	Pemba South	Dar Es Salaam	1.62 (0.21)
ANC		Pemba North	Dar Es Salaam	2.09 (0.21)
PNC		Pemba South	Dar Es Salaam	2.85 (0.47)

Outcome	**Year**	**Worst performing Region (Reference)**	**Best performing region**	**Model coefficient (±SD)**
Rwanda				
SBA	2005	Gikongoro	Kigali	2.53 (0.17)
ANC		Kigali Ngali	Cyangugu	1.03 (0.22)
PNC		Gikongoro	Kigali	2.49 (0.17)
SBA	2010	North	South	0.15 (0.08)
ANC		Kigali	South	0.08 (0.09)
PNC		Kigali	South	-0.65 (0.22)
SBA	2014	North	South	-0.13 (0.16)
ANC		Kigali	South	0.49 (0.09)
PNC		Kigali	South	0.37 (0.18)
Outcome	**Year**	**Worst performing Region (Reference)**	**Best performing region**	**Model coefficient (±SD)**
Uganda				
SBA	2000	Northern	Central	-0.72 (0.12)
ANC		Northern	Central	0.38 (0.11)
PNC		Northern	Central	1.78 (0.12)
SBA	2006	West Nile	East Central	0.91 (0.14)
ANC		North	Central 1	0.14 (0.13)
PNC		West Nile	East Central	-0.36 (0.32)
SBA	2011	Southwest	East Central	1.03 (0.13)
ANC		Central 1	Karamoja	0.23 (0.14)
PNC		Southwest	East Central	0.08 (0.21)

Table B.3 Model fit, mean posterior estimates and hyperparameters of modelled MNH outcomes.

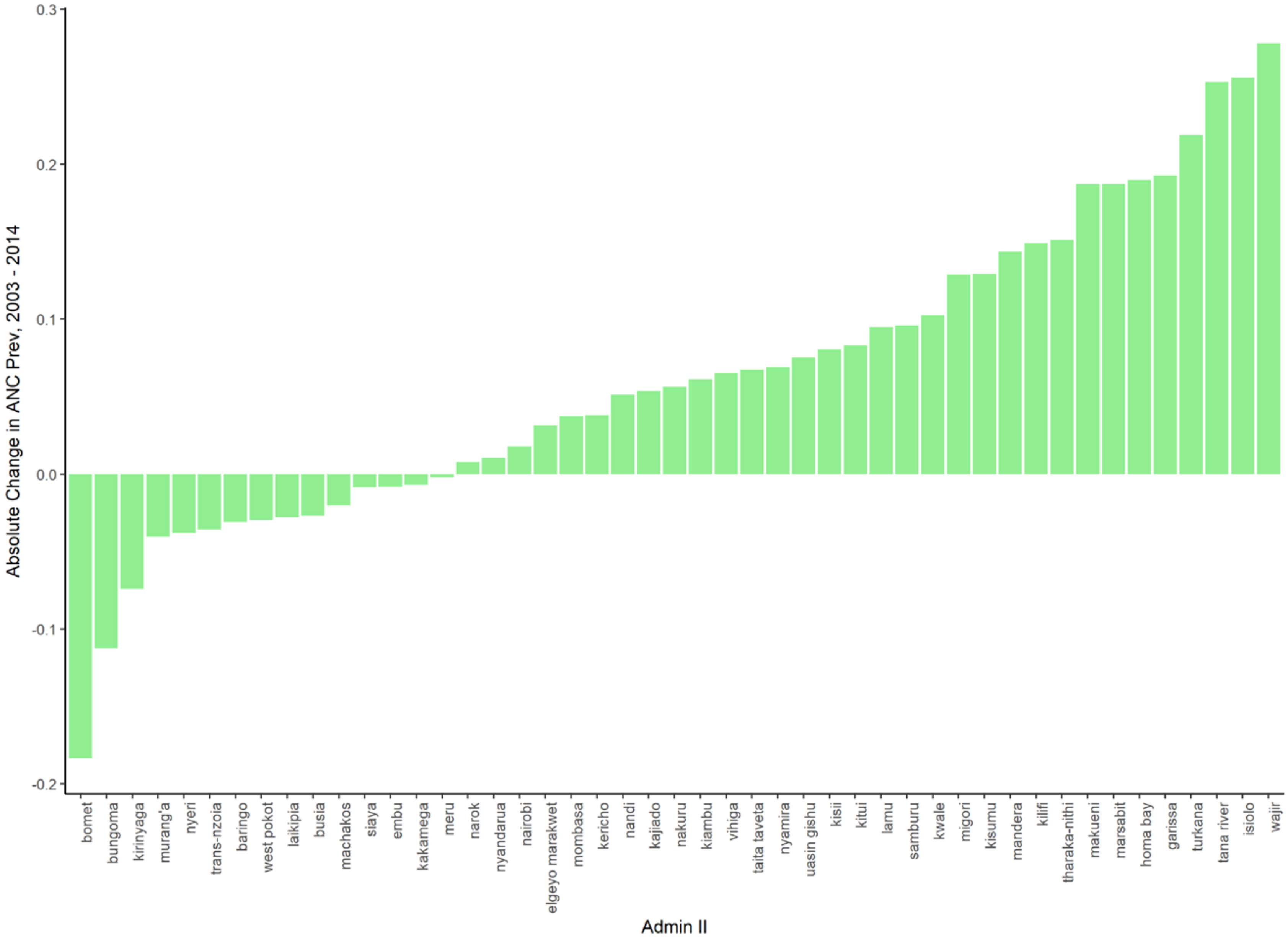
Fixed Effects	**SBA**	**ANC**	**PNC**
	Mean Posterior Estimate (SD)		
Kenya			
2003			
Intercept	7.39 (2.33)	-1.83 (2.01)	4.49 (2.57)
Rural/Urban	-0.04 (0.45)	-0.12 (0.39)	0.23 (0.5)
Education	-1.02 (0.44)	-1.1 (0.42)	-1.4 (0.48)
Wealth	-1.29 (0.57)	-0.45 (0.5)	-1.4 (0.62)
Age	-0.13 (0.07)	0.07 (0.06)	-0.07 (0.08)
Births	-2.01 (0.7)	0.24 (0.63)	-1.25 (0.77)
DIC	277.06	275.07	277.76
MLL	-141.21	-139.50	-145.49
2008			
Intercept	5.14 (2.53)	0.18 (1.93)	4.47 (2.29)
Rural/Urban	-0.51 (0.65)	-0.52 (0.46)	-0.48 (0.58)
Education	-0.32 (0.62)	-0.34 (0.42)	-0.86 (0.55)
Wealth	-1.96 (0.7)	-0.85 (0.54)	-1.82 (0.63)
Age	-0.05 (0.08)	0.03 (0.06)	-0.04 (0.07)
Births	-1.59 (0.93)	-0.19 (0.65)	-1.44 (0.85)
DIC	282.26	288.76	281.75
MLL	-148.14	-144.44	-143.96
2014			
Intercept	0.95 (3.7)	3.61 (2.56)	0.92 (3.83)
Rural/Urban	-0.16 (0.7)	-0.55 (0.46)	-0.14 (0.72)
Education	-0.67 (0.58)	-0.22 (0.42)	-0.91 (0.61)
Wealth	-2.26 (0.78)	-0.43 (0.51)	-2.29 (0.81)
Age	0.09 (0.12)	-0.09 (0.08)	0.08 (0.13)
Births	-1.16 (1.09)	-0.11 (0.72)	-0.98 (1.14)
DIC	357.55	361.77	356.08
MLL	-205.56	-197.33	-205.71
Fixed Effects	**SBA**	**ANC**	**PNC**
	Mean Posterior Estimate (SD)		
Tanzania			
1999			
Intercept	3.97 (1.48)	2.18 (1.13)	4.25 (1.39)
Rural/Urban	-0.96 (0.32)	0.01 (0.24)	-0.61 (0.31)
Education	-1.48 (0.54)	-0.56 (0.4)	-1.55 (0.5)
Wealth	-1.05 (0.42)	-0.37 (0.33)	-1.21 (0.4)
Age	-0.02 (0.05)	-0.001 (0.04)	-0.01 (0.05)
Births	-1.27 (0.41)	-0.83 (0.32)	-1.47 (0.39)
DIC	422.80	422.09	414.53
MLL	-163.80	-151.68	-156.03
2010			
Intercept	6.94 (1.31)	1.44 (0.9)	7.55 (1.39)
Rural/Urban	-0.87 (0.34)	-0.43 (0.23)	-0.93 (0.36)
Education	-1.81 (0.56)	-0.27 (0.39)	-2.04 (0.59)
Wealth	-1 (0.44)	-0.5 (0.31)	-0.93 (0.46)
Age	-0.08 (0.04)	0.04 (0.03)	-0.1 (0.04)
Births	-1.92 (0.38)	-1.48 (0.27)	-1.74 (0.4)
DIC	644.04	652.56	638.43

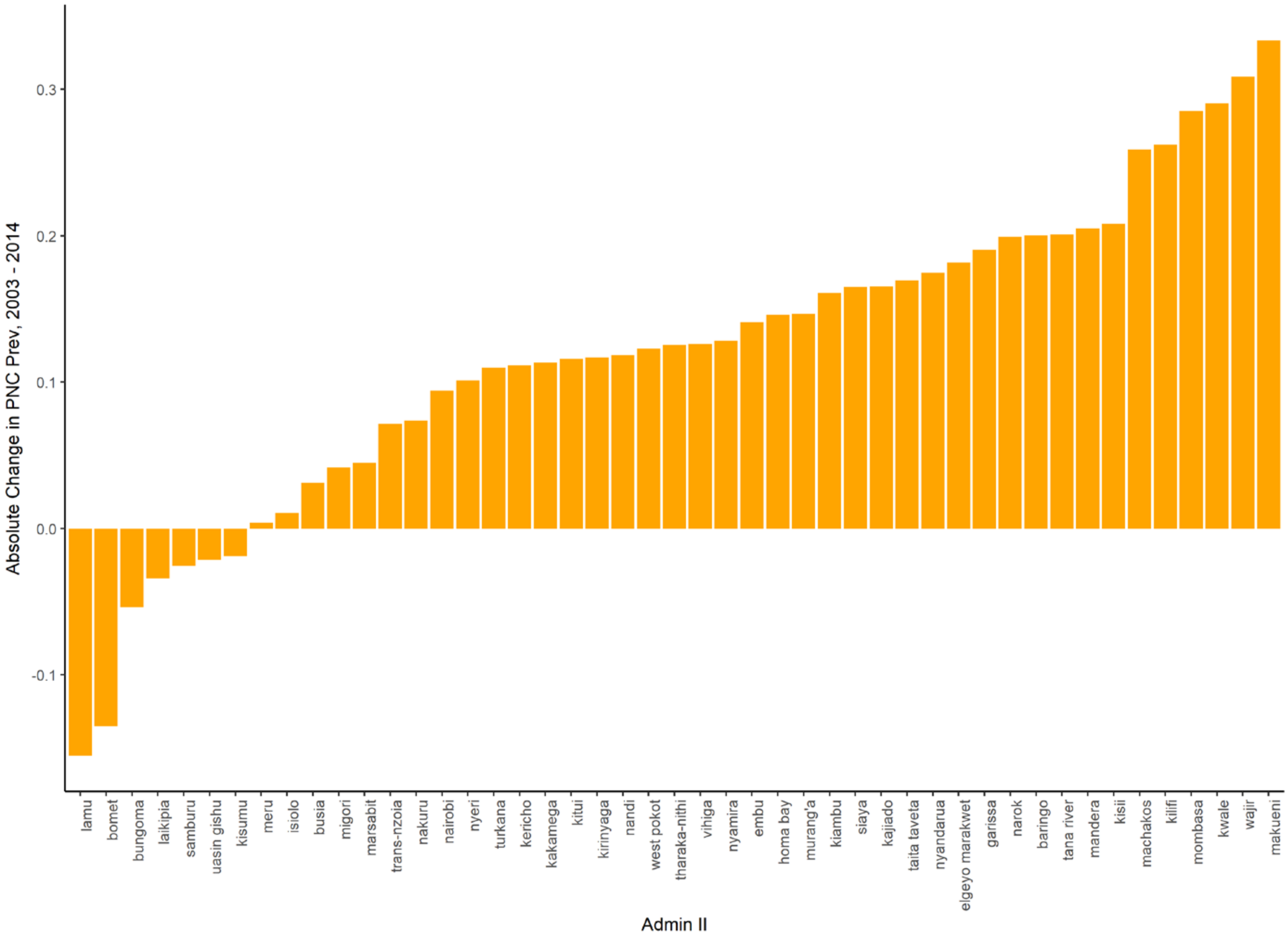
MLL	-297.88	-280.60	-299.45
2015			
Intercept	4.41 (1.21)	2.07 (0.95)	7.25 (1.47)
Rural/Urban	-0.46 (0.28)	-0.24 (0.21)	-0.68 (0.34)
Education	-2.52 (0.56)	0 (0.44)	-3.3 (0.66)
Wealth	-0.72 (0.35)	-0.53 (0.28)	-0.64 (0.42)
Age	0 (0.04)	0.01 (0.03)	-0.03 (0.05)
Births	-1.69 (0.35)	-1.29 (0.28)	-2.59 (0.42)
DIC	682.95	715.99	641.95
MLL	-312.88	-318.71	-298.86
Rwanda			
2005			
Intercept	1.32 (2.15)	-5.84 (2.68)	0.32 (2.21)
Rural/Urban	-1.43 (0.34)	-0.29 (0.4)	-1.57 (0.35)
Education	-1.9 (0.92)	-2.92 (1.17)	-1.57 (0.94)
Wealth	0 (31.62)	0 (31.62)	0 (31.62)
Age	0.02 (0.05)	0.05 (0.07)	0.05 (0.05)
Births	-0.63 (0.75)	2.13 (0.91)	-0.59 (0.76)
DIC	169.60	144.47	170.54
MLL	-79.95	-65.33	-80.75
2010			
Intercept	0.96 (3.07)	-3.4 (3.39)	2.94 (3.06)
Rural/Urban	-0.7 (0.63)	-1.22 (0.66)	-0.03 (0.63)
Education	-1.66 (1.19)	-1.05 (1.33)	-2.02 (1.18)
Wealth	-0.98 (0.95)	1.76 (0.99)	-1.24 (0.96)
Age	0.03 (0.08)	0.14 (0.09)	-0.01 (0.08)
Births	0.05 (1.01)	-0.69 (1.1)	-0.77 (1.01)
DIC	181.69	182.98	180.2
MLL	-93.78	-96.71	-92.80
2014			
Intercept	-0.82 (4.49)	-3.64 (2.66)	0.84 (3.97)
Rural/Urban	-0.67 (1)	-0.45 (0.57)	1.11 (0.87)
Education	-4.75 (2.42)	-2.73 (1.42)	-1.18 (2.15)
Wealth	-0.33 (1.45)	1.48 (0.89)	-1.57 (1.33)
Age	0.11 (0.13)	0.05 (0.07)	0.06 (0.11)
Births	1.11 (1.85)	1.52 (1.06)	-0.31 (1.6)
DIC	137.26	179.75	148.89
MLL	-64.22	-90.14	-72.30

Fixed Effects	**SBA**	**ANC**	**PNC**
	Mean Posterior Estimate (SD)		
Uganda			
2000			
Intercept	-0.7 (1.49)	0.91 (1.11)	4.61 (1.28)
Rural/Urban	-1.18 (0.37)	-0.87 (0.29)	-1.72 (0.34)
Education	-0.91 (0.67)	-0.61 (0.49)	-1.25 (0.55)
Wealth	0.48 (0.3)	-0.15 (0.23)	0.07 (0.25)
Age	-0.02 (0.05)	0 (0.03)	-0.08 (0.04)
Births	0.48 (0.44)	-0.13 (0.33)	-0.47 (0.37)
DIC	355.28	394.81	374.86
MLL	-115.51	-129.15	-121.04
2006			
Intercept	2.59 (1.17)	0.54 (0.88)	2.55 (1.19)

Rural/Urban	-1.39 (0.53)	-0.6 (0.32)	-1.01 (0.54)
Education	-0.99 (0.54)	-0.06 (0.38)	-0.96 (0.56)
Wealth	-1.07 (0.42)	-0.07 (0.29)	-1.3 (0.44)
Age	0.01 (0.04)	0.02 (0.03)	0.02 (0.04)
Births	-0.81 (0.37)	-0.43 (0.3)	-0.99 (0.38)
DIC	420.75	444.63	417.22
MLL	-142.35	-144.13	-142.13
2011			
Intercept	1.86 (1.18)	0.46 (0.93)	1.63 (1.06)
Rural/Urban	-1.47 (0.4)	-0.45 (0.29)	-0.55 (0.34)
Education	-0.85 (0.52)	0.96 (0.4)	-0.43 (0.48)
Wealth	-1.39 (0.49)	-0.54 (0.36)	-1.26 (0.43)
Age	0.04 (0.03)	-0.01 (0.03)	0 (0.03)
Births	-0.36 (0.35)	0.1 (0.3)	-0.4 (0.33)
DIC	453.70	483.55	476.54
MLL	-161.03	-166.45	-169.32
Hyperparameter (Spatial Precision)	**SBA**	**ANC**	**PNC**
	Mean Posterior Estimate (SD)		
Kenya			
2003	5.1 (1.8)	6.2 (2.2)	3.6 (1.1)
2008	3.5 (1.1)	8.0 (3.2)	4.8 (1.7)
2014	6.9 (6.4)	14.1 (9.2)	6.9 (4.9)
Tanzania			
1999	2.0 (0.6)	5.8 (2.6)	2.5 (0.8)
2010	2.0 (0.4)	5.6 (1.5)	1.8 (0.4)
2015	3.1 (0.6)	5.6 (1.3)	2.1 (0.4)
Rwanda			
2005	36.7 (53.5)	111.4 (424.9)	25.9 (29.8)
2010	8.29 (4.6)	5.9 (2.7)	8.6 (4.7)
2014	6.9 (6.4)	14.1 (9.2)	6.9 (4.9)
Uganda			
2000	1.2 (0.4)	2.8 (1.1)	1.9 (0.7)
2006	2.6 (0.9)	26.0 (33.8)	2.2 (0.7)
2011	2.2 (0.7)	10.6 (6.7)	3.5 (1.5)

B.2 Chapter 5 Supplementary Figures




Absolute Change in PNC Prev, 2003 - 2014
0.3
0.2
0.1
0.0
-0.1
Admin II
lamu
bomet
bungoma
laikipia
samburu
uasin gishu
kisumu
meru
isiolo
busia
migori
marsabit
trans-nzoia
nakuru
nairobi
nyeri
turkana
kericho
kakamega
kitui
kirinyaga
nandi
west pokot
tharaka-nithi
vihiga
nyamira
embu
homa bay
murang'a
kiambu
siaya
kajiado
taita taveta
nyandarua
elgeyo marakwet
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baringo
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mandera
kisii
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kilifi
mombasa
kwale
wajir
makueni

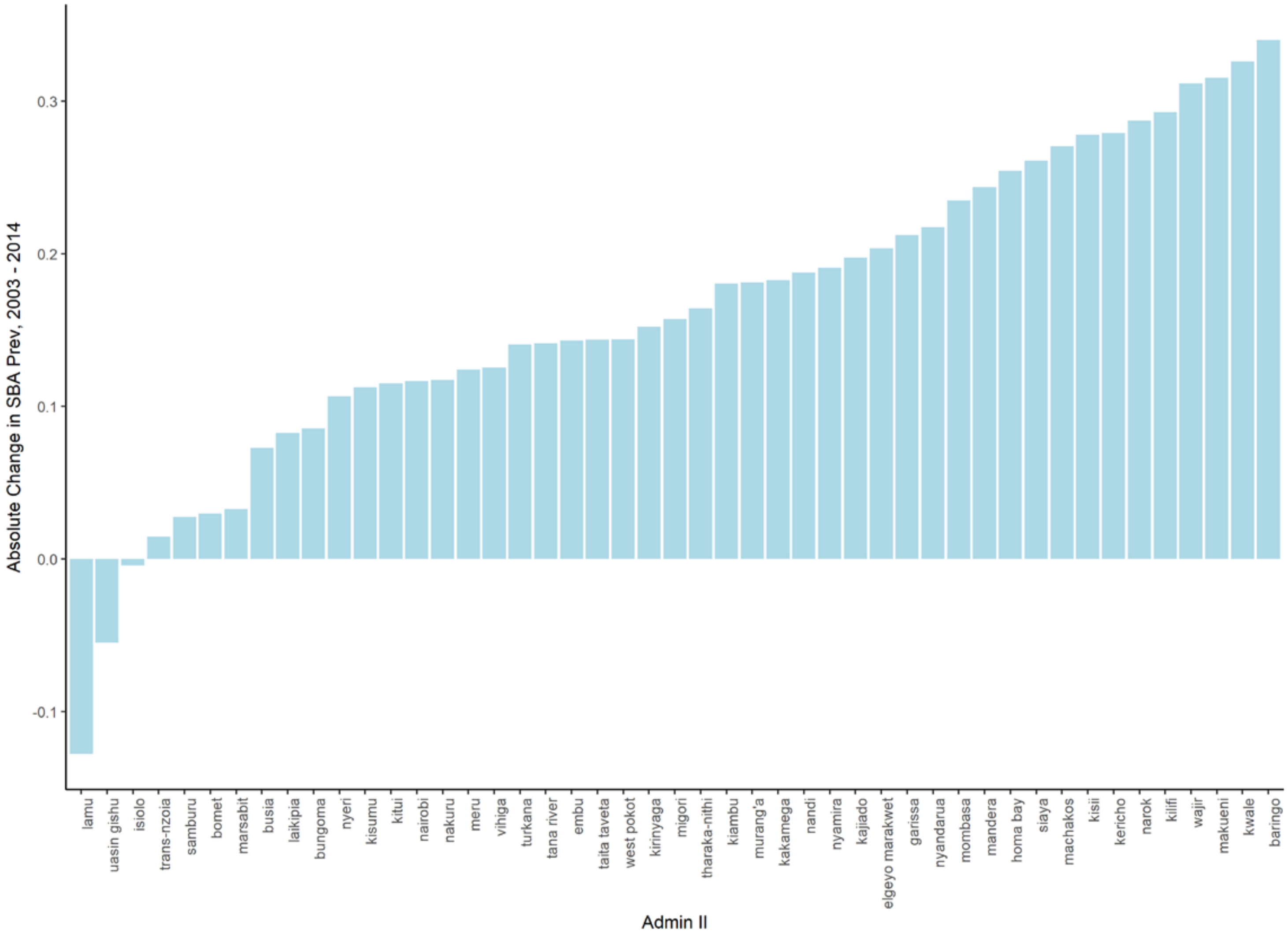
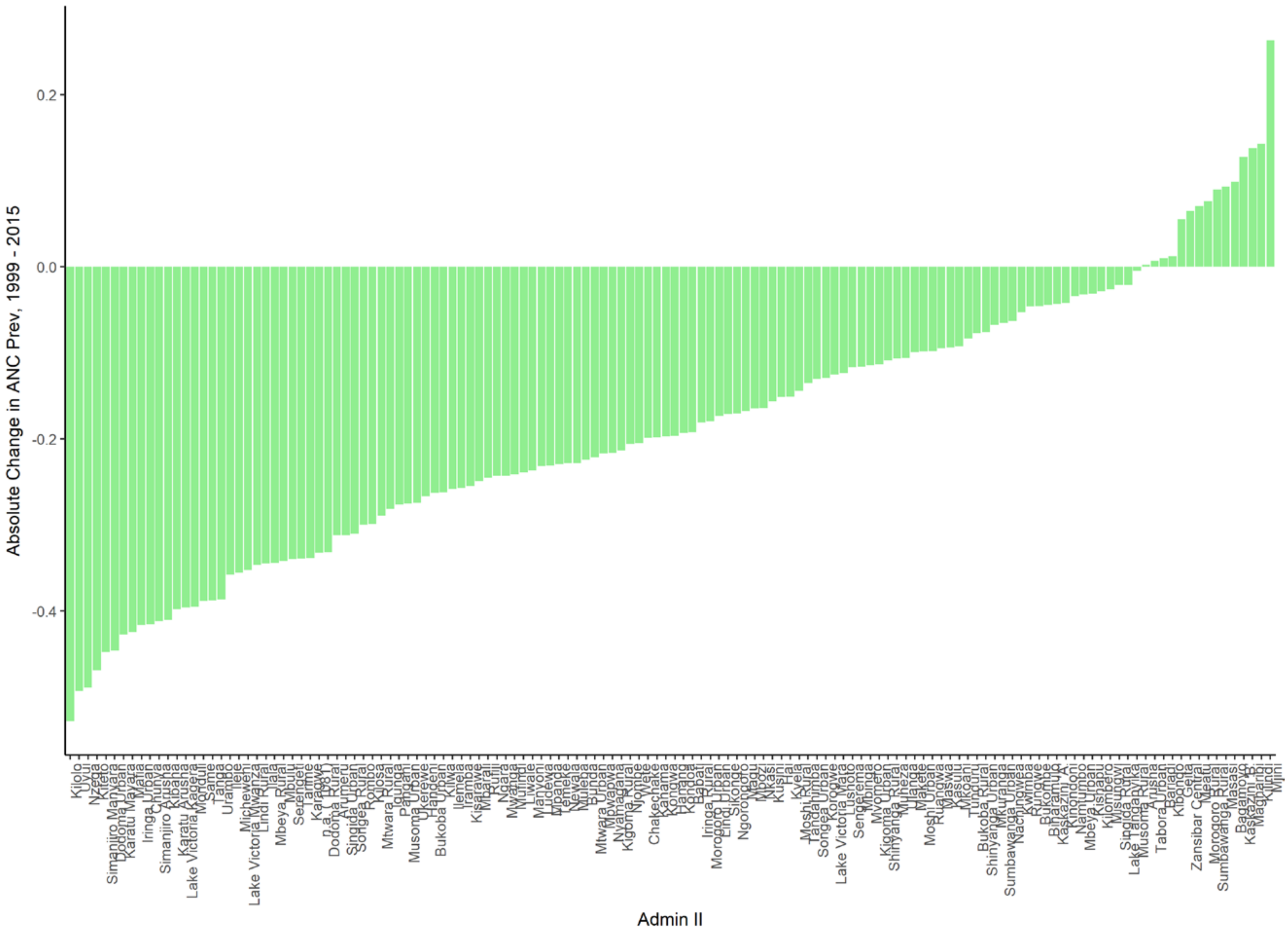
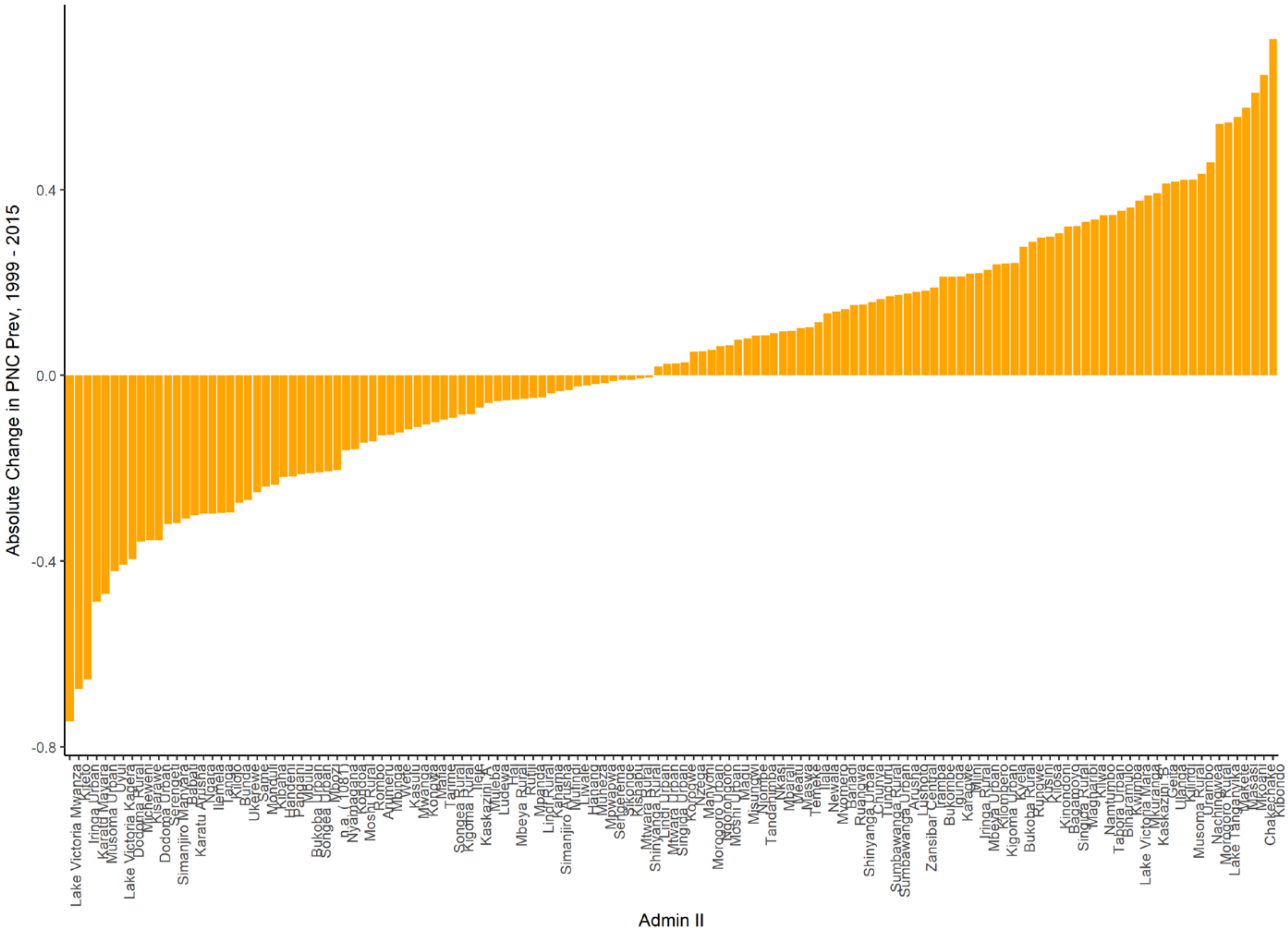


Figure B.3 Absolute change in a) 4+ antenatal care visits (green), b) postnatal care check-up within 48 hours (red), and c) skilled birth attendance (blue), Kenya DHS data, 2003 – 2014, ordered by administrative II unit.


Absolute Change in ANC Prev, 1999 - 2015
0.2
0.0
-0.2
-0.4
Admin II


Absolute Change in PNC Prev, 1999 - 2015
0.4
0.0
-0.4
-0.8
Admin II

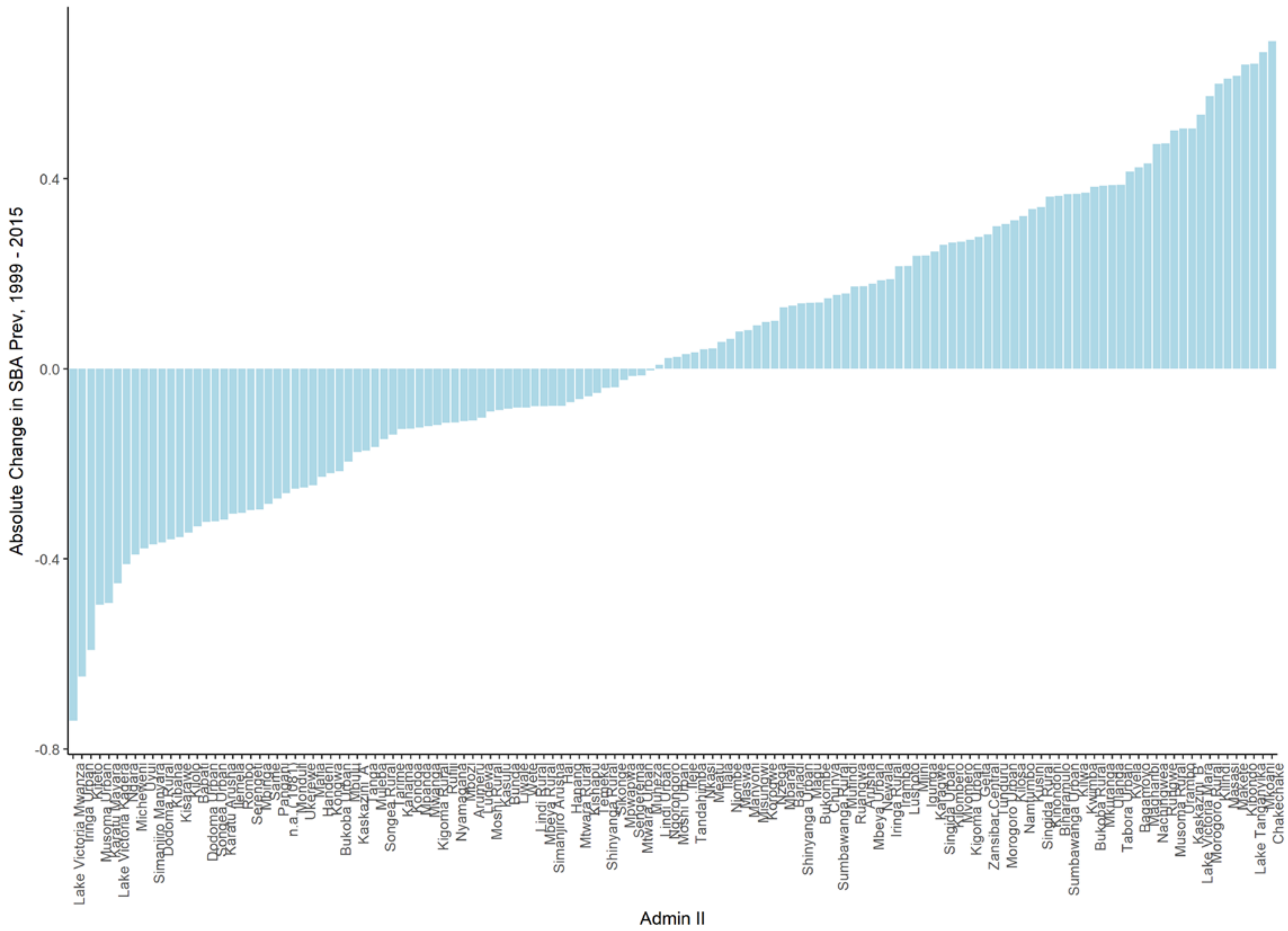
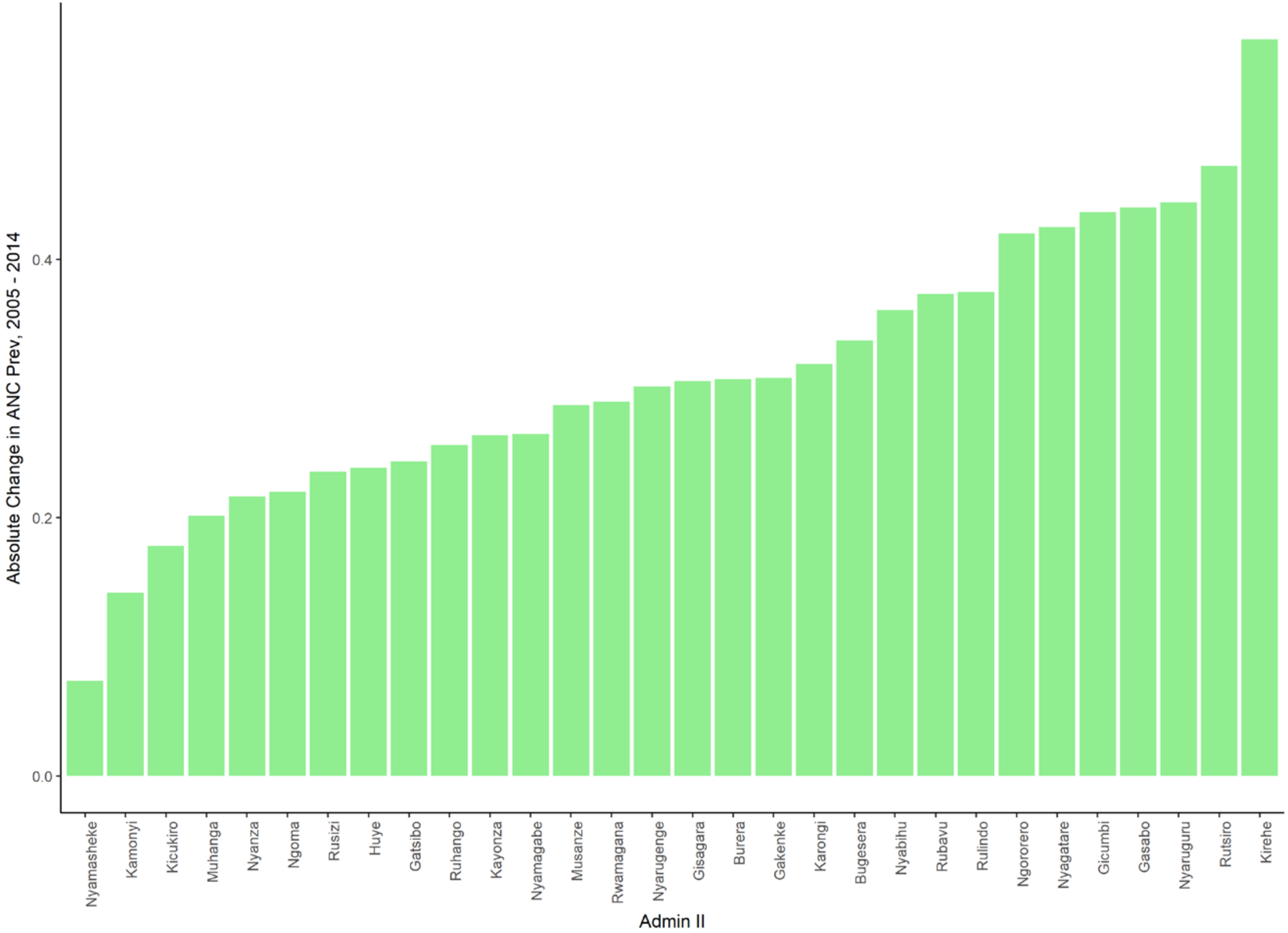
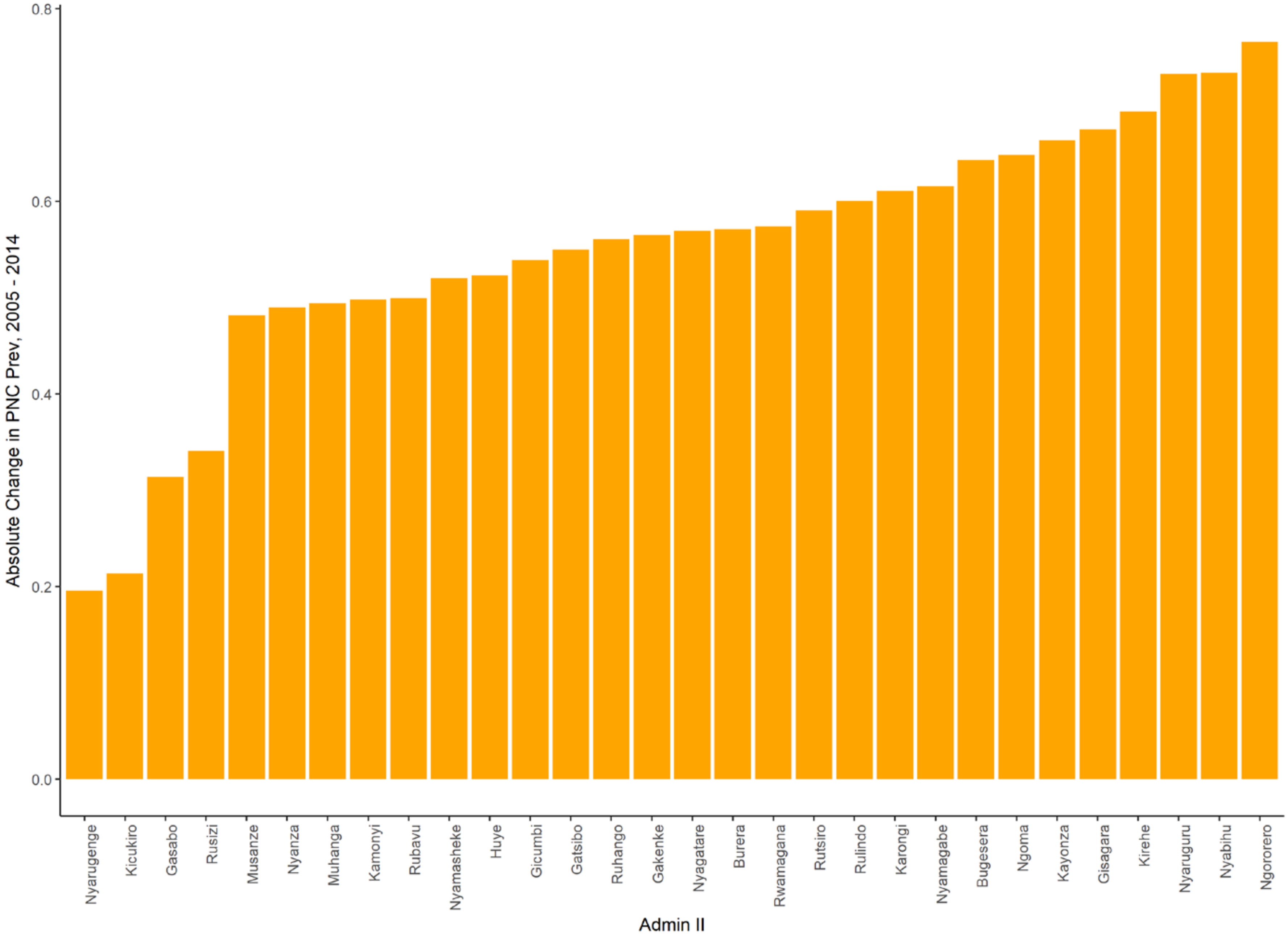


Figure B.4 Absolute change a) 4+ antenatal care visits (green), b) postnatal care check-up within 48 hours (red), and c) skilled birth attendance (blue), Tanzania DHS data, 1999 – 2015, ordered by administrative II unit.


Absolute Change in ANC Prev, 2005 - 2014
0.0
0.2
0.4
Nyamasheke
Kamonyi
Kicukiro
Muhanga
Nyanza
Ngoma
Rusizi
Huye
Gatsibo
Ruhango
Kayonza
Nyamagabe
Musanze
Rwamagana
Nyarugenge
Gisagara
Burera
Gakenke
Karongi
Bugesera
Nyabihu
Rubavu
Rulindo
Ngororero
Nyagatare
Gicumbi
Gasabo
Nyaruguru
Rutsiro
Kirehe
Admin II


Absolute Change in PNC Prev, 2005 - 2014
0.8
0.6
0.4
0.2
0.0
Nyarugenge
Kicukiro
Gasabo
Rusizi
Musanze
Nyanza
Muhanga
Kamonyi
Rubavu
Nyamasheke
Huye
Gicumbi
Gatsibo
Ruhango
Gakenke
Nyagatare
Burera
Rwamagana
Rutsiro
Rulindo
Karongi
Nyamagabe
Bugesera
Ngoma
Kayonza
Gisagara
Kirehe
Nyaruguru
Nyabihu
Ngororero
Admin II

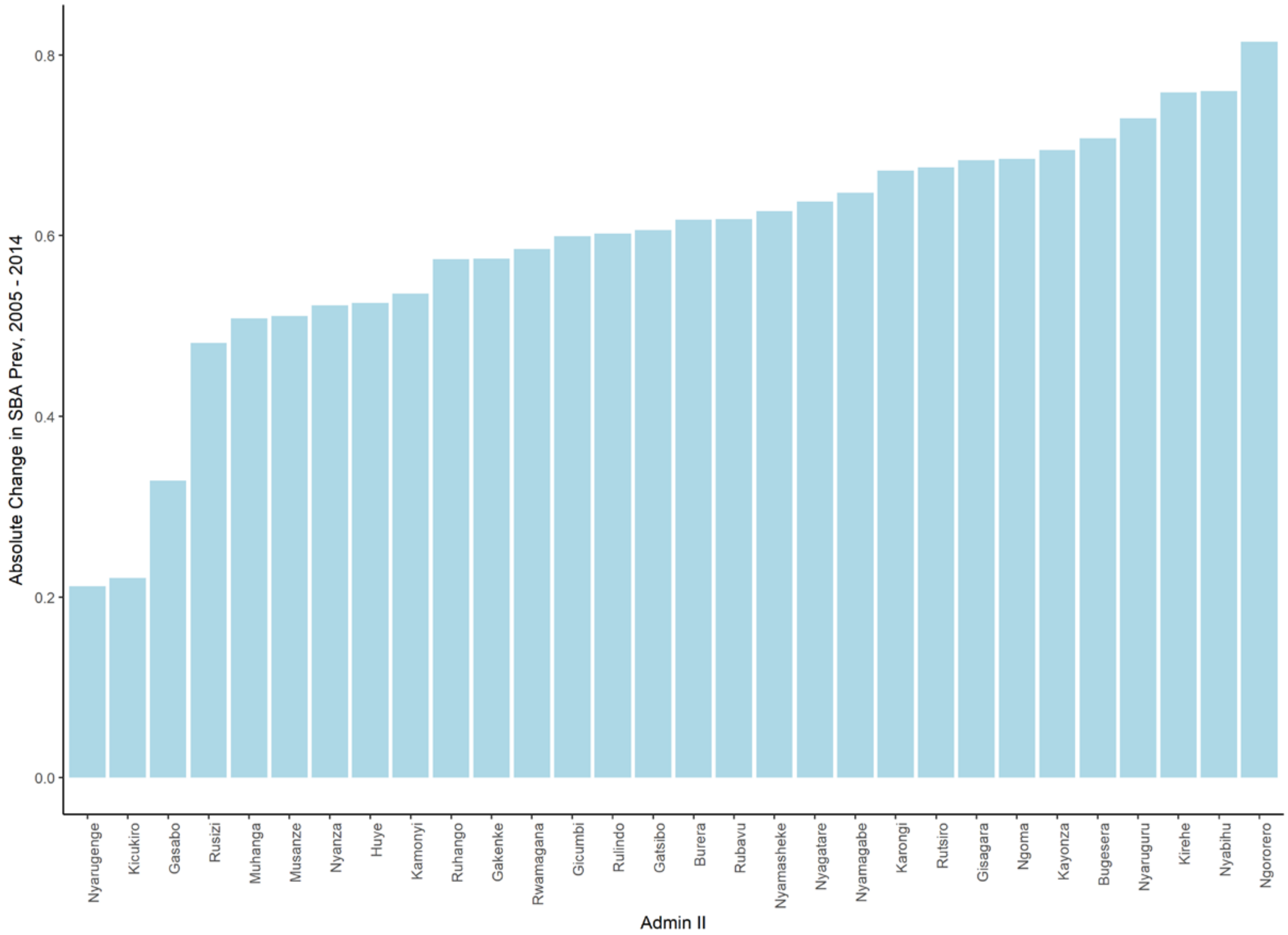
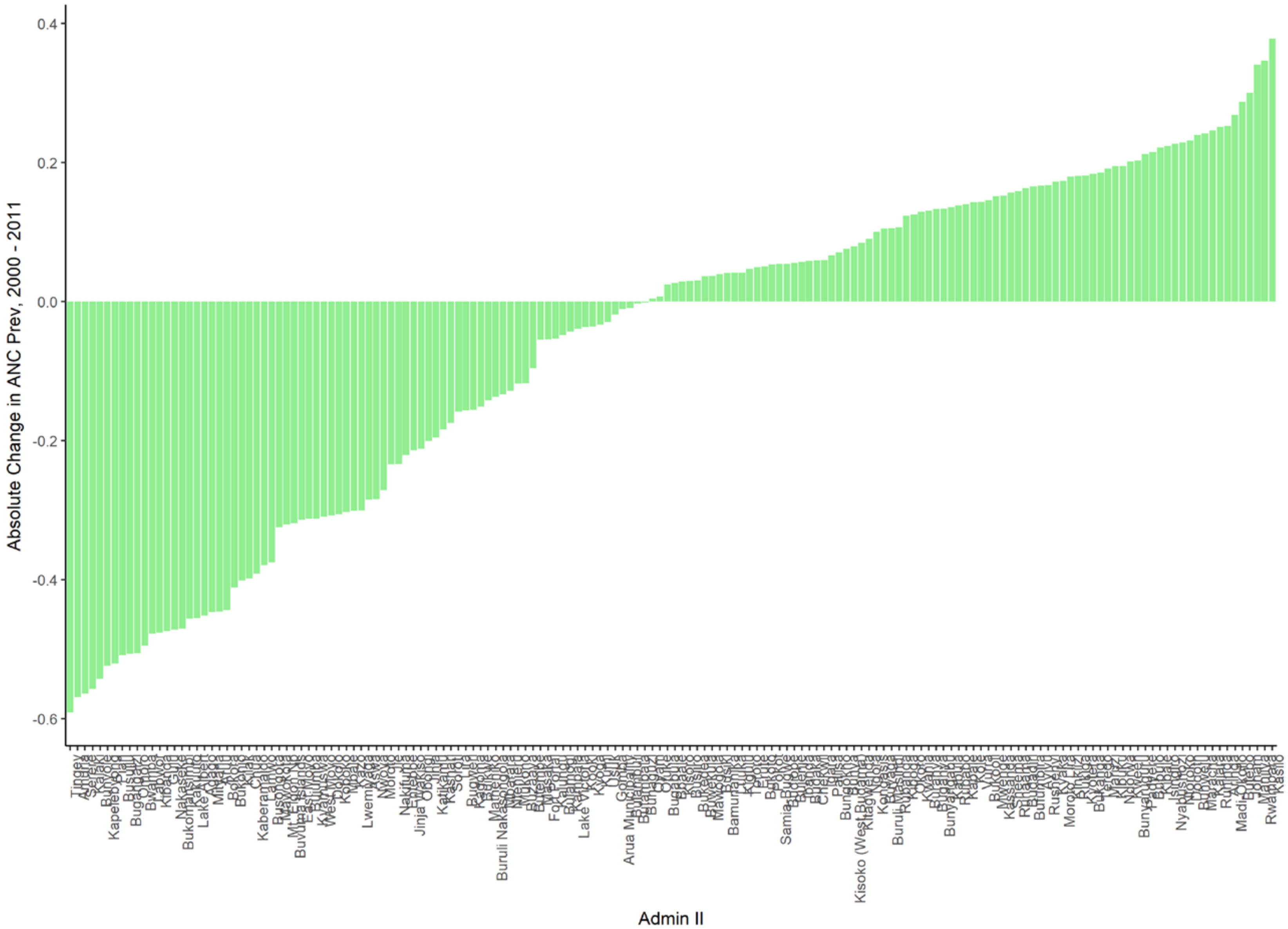
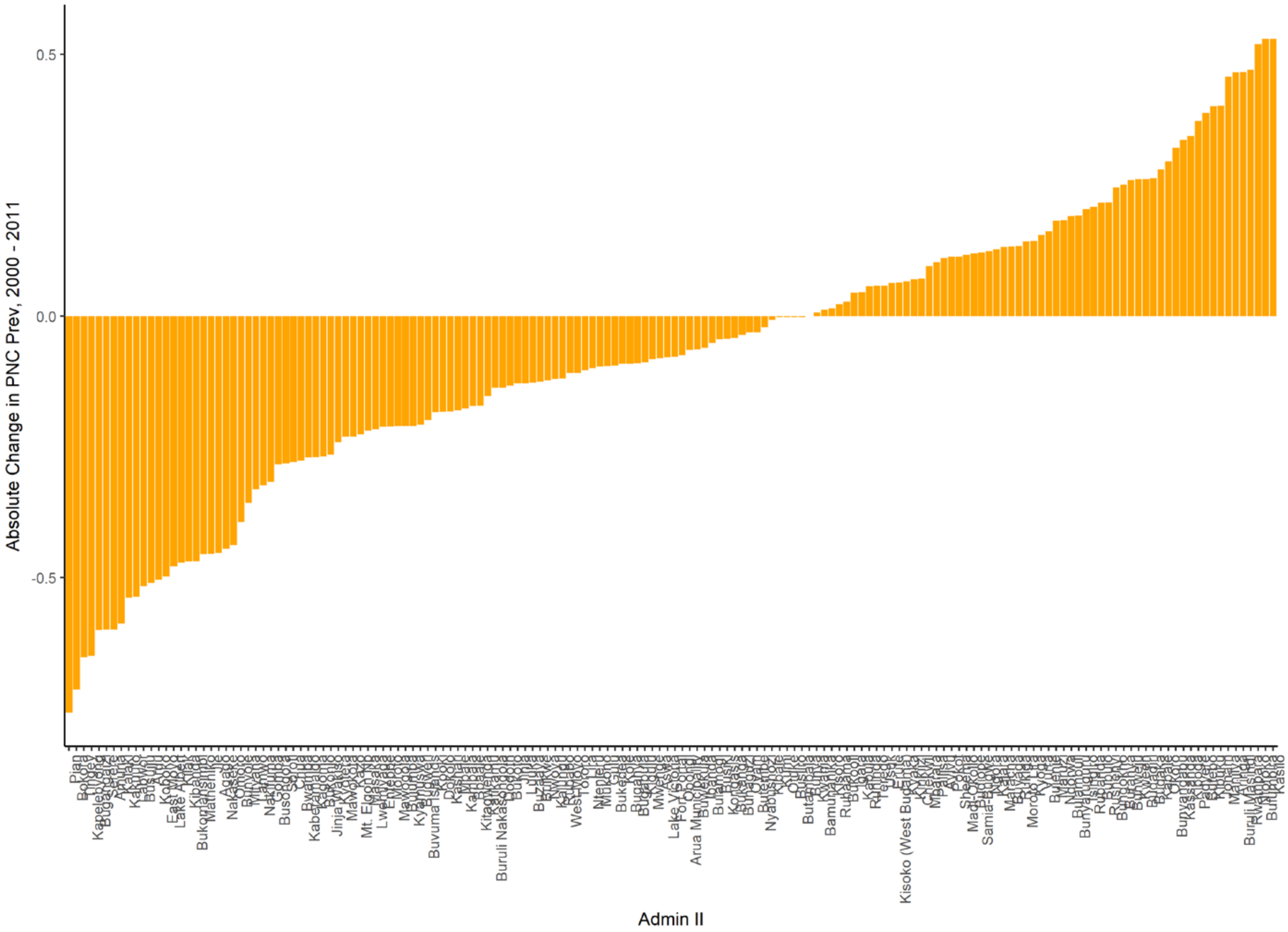


Figure B.5 Absolute change a) 4+ antenatal care visits (green), b) postnatal care check-up within 48 hours (red), and c) skilled birth attendance (blue), Rwanda DHS data, 2005 – 2014, ordered by administrative II unit.


0.4
0.2
0.0
-0.2
-0.4
-0.6
Absolute Change in ANC Prev, 2000 - 2011
Admin II


Absolute Change in PNC Prev, 2000 - 2011
0.5
0.0
-0.5
Admin II

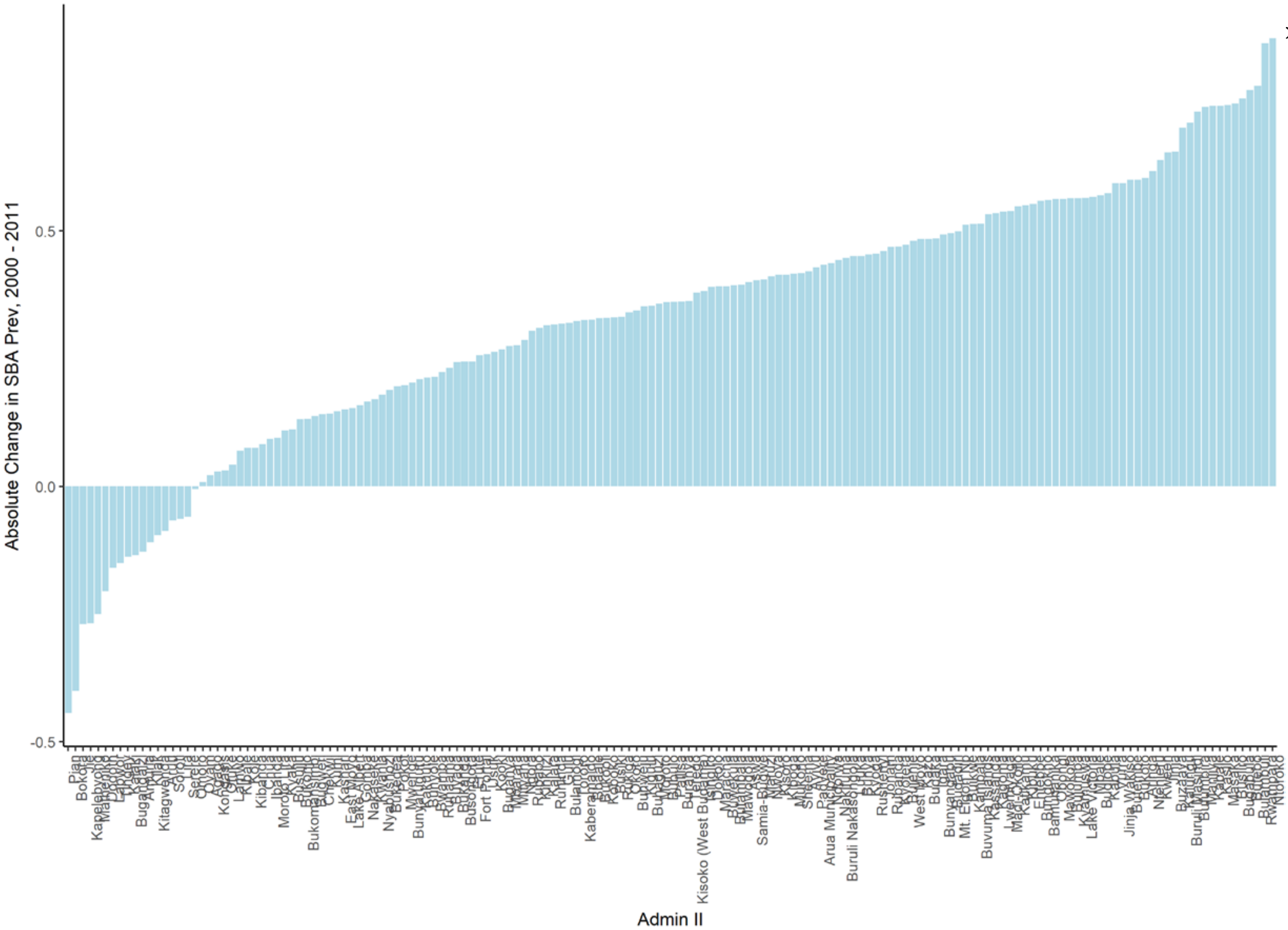
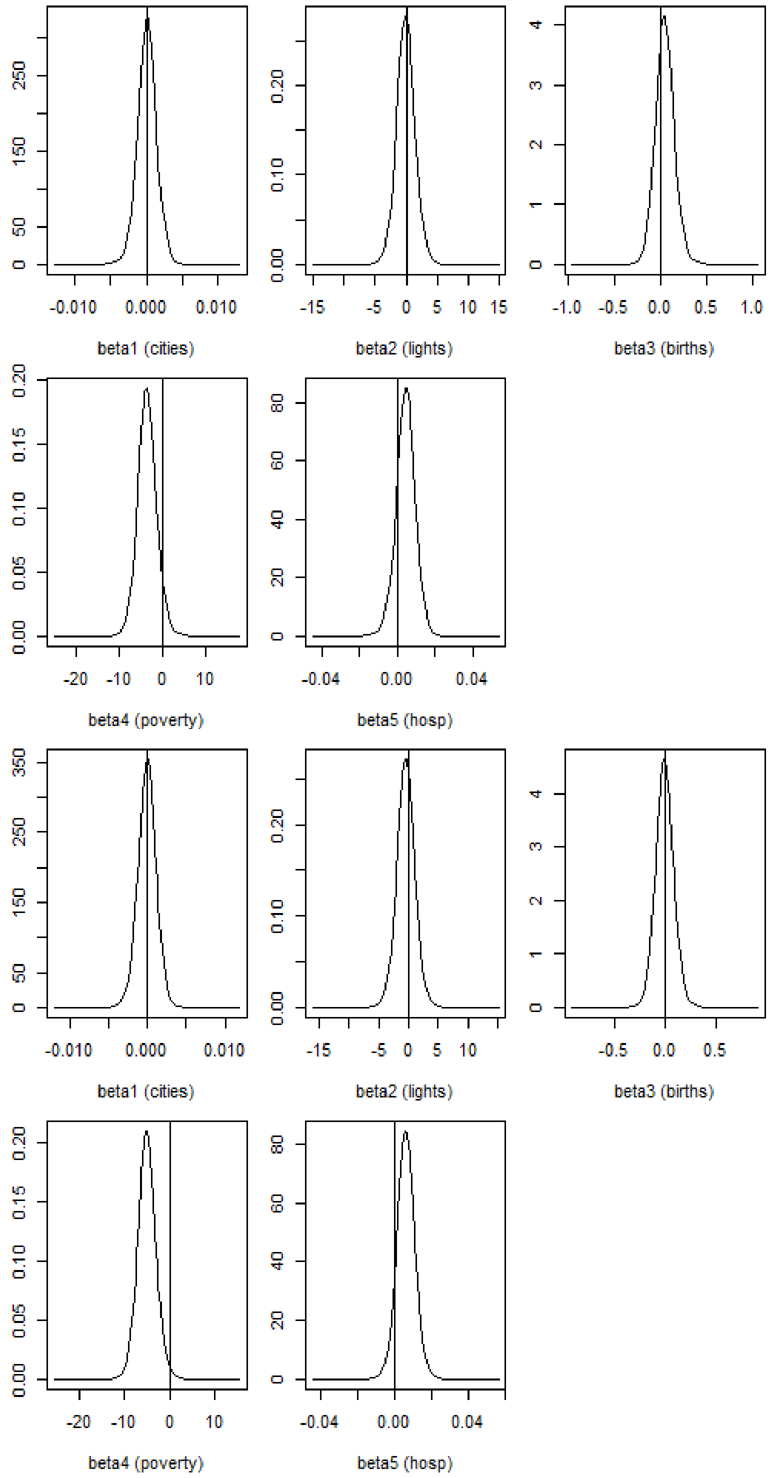


Figure B.6 Absolute change in a) 4+ antenatal care visits (green), b) postnatal care check-up within 48 hours (red), and c) skilled birth attendance (blue), Uganda DHS data, 2000 – 2011, ordered by administrative II unit.

Appendix C Chapter 6 Appendix

C.1 Chapter 6 Supplementary Figures



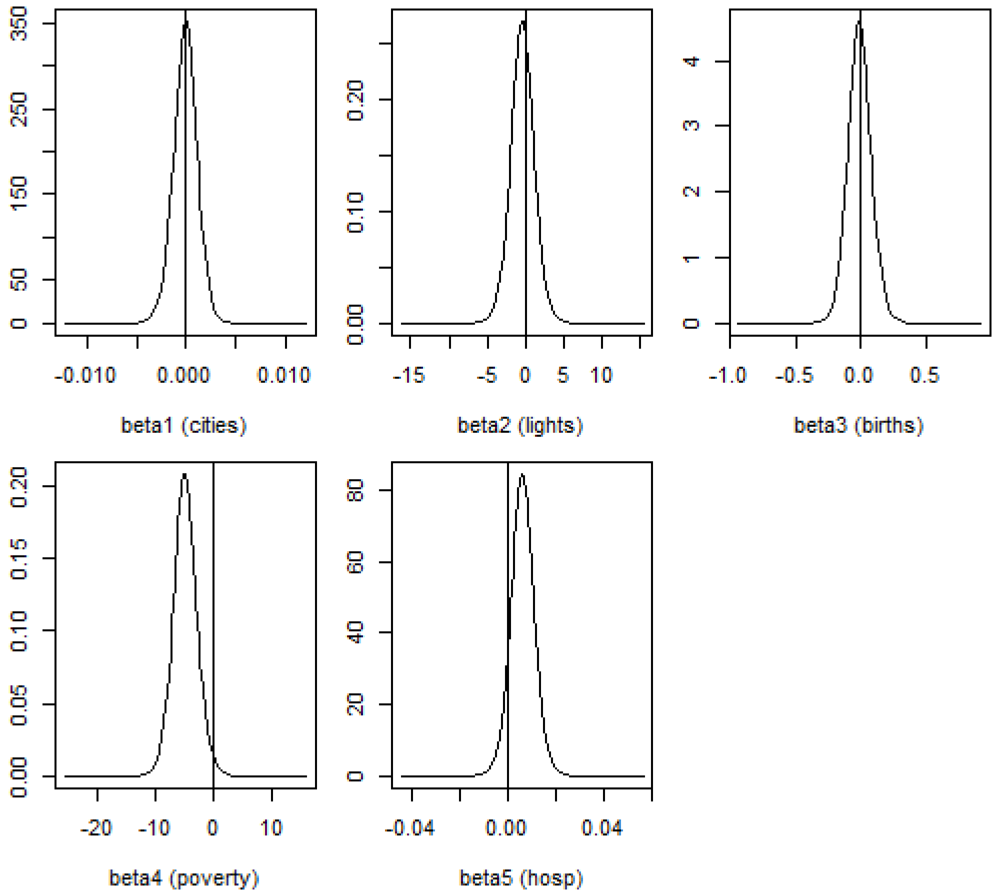


Figure C.7 Marginal effect density plots at 5km (top), 50km (middle), and 100km (bottom)

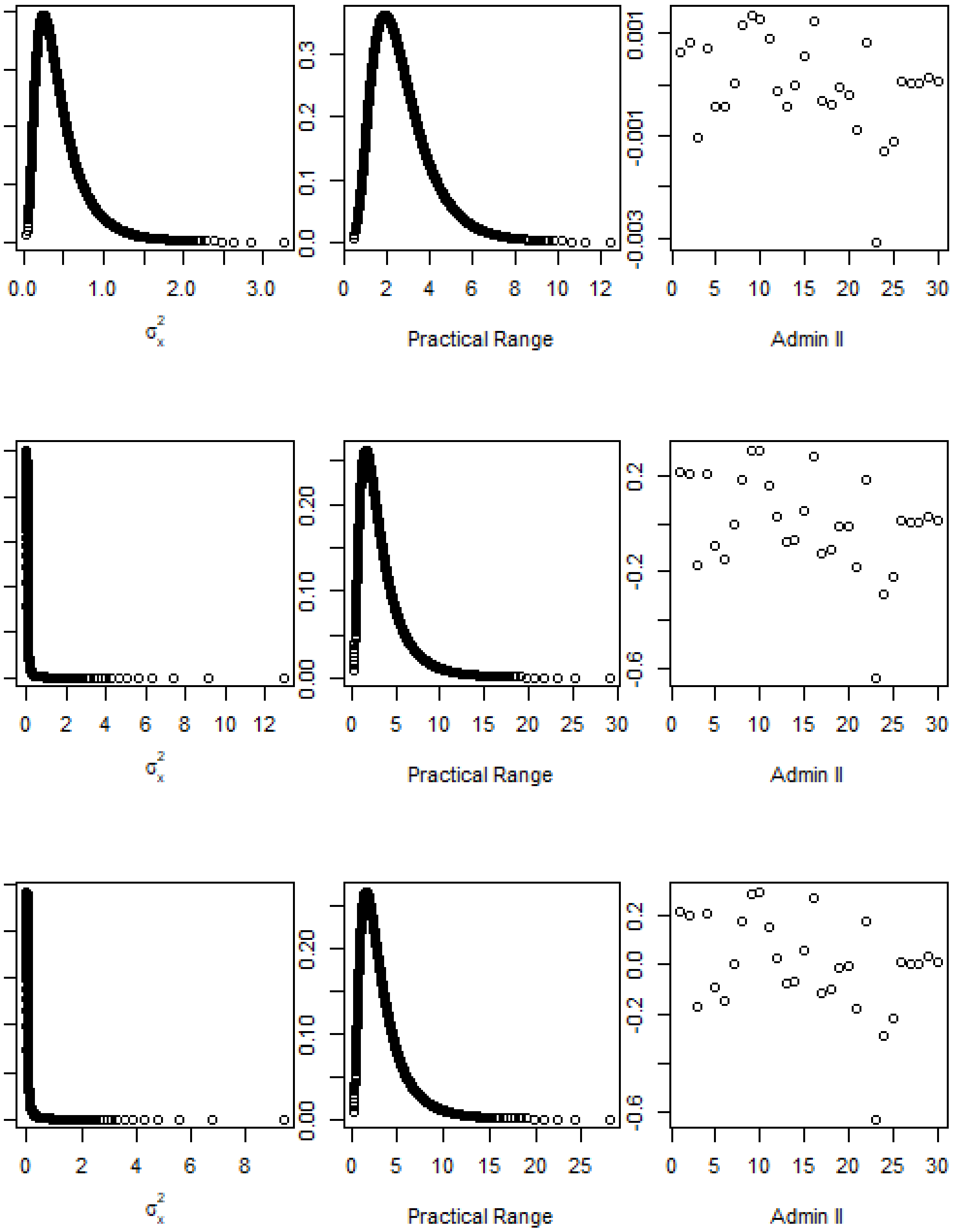


Figure C.8. Model variance, model range, and model random effects at the 5km (top), 10km (middle) and 100km (bottom) scales.

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